How far has Basel III regulation affected the key banking sector variables in Bangladesh?

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A thesis submitted in partial fulfilment of the requirements of Nottingham Trent University for the degree of Doctor of Philosophy

September 2022

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Declaration

This thesis has been submitted following the rules and regulations of Nottingham Trent University. I hereby declare that this thesis contains no material published previously by any other author apart from where due acknowledgement has been made. I also declare that no material contained in the thesis has been used in any other submission for an academic award. However, this thesis has three main objectives, and each objective has been produced as a separate paper. The author has submitted two objectives as two separate papers to two academic journals for publication. The first paper produced was submitted in October 2021, and the second was submitted in July 2022. The invitation for submission came after presenting them at an annual conference, and both are under review now.

List of papers under review from this thesis

Sheikh, M.H., Hauck, A., Liu, L., and Wu, Z., (under review) Basel III liquidity and bank capital: How far has this regulation affected the cost efficiency of banks in Bangladesh. *Economic Modelling.*

Sheikh, M.H., Hauck, A., Liu, L., and Wu, Z., (under review) Basel III Implementation: Effect on Bank Return in Bangladesh. *Open Economies Review.*

Abstract

This study started by examining the correlation between liquidity risk and bank capital, which are the key regulatory changes of Basel III. Then it examined the effect of liquidity risk and bank capital on bank return, cost efficiency, and the growth of banks and Non-Bank Financial Institutions (NBFIs) in Bangladesh. The cost efficiency of banks and the effect of liquidity risk and bank capital on cost efficiency have been investigated following a two-step approach. The cost efficiency has been estimated using the Stochastic Frontier Analysis (SFA), and the effect has been estimated by applying the Generalised Method of Moments (GMM) with Instrumental Variables (IV). The correlation between the liquidity risk and bank capital and their effect on bank return has also been examined using IV GMM. The growth of banks and the differential impact on NBFIs' growth have been investigated by applying the pooled Ordinary Least Square (OLS) and Random Effect (RE) models following the difference-in-difference treatment effect. A balanced panel data of banks and NBFIs from 2011 to 2019 has been applied in this study, whereas the country has been following Basel III since 2015. This study has applied four different measures of liquidity risk, and they have been found homogeneous. The results show that banks with higher capital ratios hold less liquidity, indicating a higher liquidity risk. The year fixed effect results show no significant change in banks' liquidity position, but the bank return and cost efficiency decreased after implementing Basel III in the country. The liquidity risk is found homogeneous to bank return and cost efficiency, but it is not related to the growth of banks and NBFIs. On the other hand, bank capital is positively related to bank return and negatively related to the cost efficiency and growth of banks and NBFIs in the country. The difference-in-difference treatment effect illustrates that NBFIs' growth in lending share from 2015 to 2019 is significantly lower than banks.

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Glossary

BCBS: Basel Committee on Banking Supervision
CAR: Capital to Assets ratio
CET1: Common Equity Tier 1
CFPB: Consumer Financial Protection Bureau
DSGE: Dynamic Stochastic General Equilibrium
FE: Fixed Effect
FGAP: The difference between deposits and loan
GMM: Generalised Method of Moments
IV: Instrumental Variable
LA/TA: Liquid Assets to Total Assets
LCR: Liquidity Coverage Ratio
LLP/TL: Loan Loss Provision to Total Loan
LLR/TL: Loan Loss Reserve to Total Loan
LNTA: Natural logarithm of Total Assets
NBFIs: Non-Bank Financial Institutions
NETL/C&SF: Net Loan to Customer and Short-term Funding
NIM: Net Interest Margin
NL/TA: Net Loan to Total assets
NPL: Non-Performing Loan
NSFR: Net Stable Funding Ratio
OLS: Ordinary Least Square
RCAR: Required Capital Assets ratio
RE: Random Effect
ROA: Return on Assets
ROE: Return on Equity
SFA: Stochastic Frontier Analysis
SRM: Single Resolution Mechanism
SSM: Single Supervisory Mechanism
TC: Total Costs
TE: Technical Efficiency
TRE: True Random Effect

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1. Introduction

The importance of banks' liquidity risk drew special attention during the last financial crisis, which was officially announced in December 2007 in the USA (National Bureau of Economic Research, 2010). The crisis in the banking sector started in September 2008 with Lehman Brothers' bankruptcy, the fourth largest investment bank in America, founded in 1847. The financial institution failed because of having substantial illiquid assets from the subprime mortgage. Lehman Brothers filed the petition for bankruptcy on the 15th of September 2008, and on the 17th of September, the withdrawal from the 'Money Market Fund' was a record of US$ 196 billion (Fein, 2012). To mitigate the effect of this crisis, the US Federal Reserve took numerous initiatives, including 'liquidity provision to banks', 'liquidity provision to dealers', 'liquidity provision to other market participants' and 'Balance sheet implication' (Fleming, 2012). The Federal Reserve used its 'discount window' and 'open market operations' tools to provide liquidity to banks. This crisis in the banking sector sparked the 'great recession' worldwide, which ended in 2009 in the USA (National Bureau of Economic Research, 2010).

Many economists, including Drach and Cassis (2021), related the 2007-2008 financial crisis as the consequence of regulatory changes in most developed economies at the end of the twentieth century. This regulatory change was termed 'deregulation' and 'liberalisation', opposite to the previous era called the Bretton Woods system and sometimes portrayed as the period of 'financial repression'. Baltensperger and Dermine (1987) termed the deregulation in the 1980s as 'a la mode' or 'in fashion' in many countries. Because of this deregulation, new financial products or markets were advertised daily. Under the 1986 Building Society Act in the UK, building societies were allowed to turn into banking institutions. They used to be real estate and house finance centered, but after the deregulation in 1986, they were integrated into the overall financial system. It also enabled commercial banks to enter the mortgage market, which increased market competition as the commercial banks were increasing their market share in the mortgage market (Casu, 2015). Furthermore, in France, the 1983 Law on Savings Banks allowed the saving banks to provide more personal loans, and the 1984 Banking Law aimed at integrating various types of credit institutions. In the 1980s, the European community was under pressure to liberalise financial markets based on the concept that deregulation would improve savings allocation (Baltensperger and Dermine, 1987). In the USA, commercial banking was a protected industry until the 1980s. The McFadden Act of 1927 enabled the federal government to protect banks from out-of-state competition by restricting interstate branch banking. After the great depression in October 1929, the Glass-Steagall Act (1933) differentiated commercial and investment banking allowing regulators to control commercial banks tightly. Market competition in commercial banking was also restricted by Regulation Q, ceiling the interest rate on customer deposits. Acquiring banks by holding firms outside of any state was restricted by the Douglas amendments to the Bank Holding Company Act of 1956. Within-state branch banking was also restricted in many states in the USA.

In the 1980s, the Federal Reserve reinterpreted the Glass-Steagall Act, relaxed restrictions, and allowed commercial banks to do investment banking. According to Calomiris (2000), the restrictions were relaxed because commercial banks faced competitive pressure from their European counterparts and non-bank financial institutions. The restrictions on nationwide banking begin to end with the Garn-St Germain Depository Institutions Act of 1982, allowing bank holding firms to acquire banks or thrifts in other states. Then, the states relaxed restrictions on interstate and branch banking. The interest rate ceiling was also removed in the 1980s by repealing regulation Q. Cunha (2020) stated that these regulatory changes were made because of the high inflation in the 1970s that decreased people's saving in banks in the real term. The real estate lending regulation was changed in the 1980s. The Garn-St Germain Depository Institutions Act of 1982 removed the statutory restriction on real estate lending, including the maximum loan-to-value ratio. Furthermore, the Alternative Mortgage Transactions Parity Act of 1982 removed restrictions on different types of mortgages, like interest-only or adjustable-rate mortgages. According to Brunnermeier (2009), the lenders targeted low-income and high-risk borrowers, increasing the subprime loans because of these changes. This loan inflated the real estate bubble in the early 2000s and was the root cause of the 2007-2008 financial crisis (Brunnermeier, 2009). The deregulation in the 1980s led to an increase in the number of new banks in the USA; the average percentage of approved new bank applications increased by nearly 30 per cent every year compared with the 1970s. It was claimed that the deregulation would increase competition in the market, but the USA witnessed the highest number of bank failures in that decade after the great depression. The regulators took numerous initiatives to mitigate this crisis, and it raised the doctrine "too big to fail" as most failed banks were small (Baltensperger and Dermine, 1987).

Different explanations have been given for the financial deregulation in the 1980s. According to Sherman (2009), inflation and economic turmoil with the end of the Bretton Woods system in the 1970s, oil shocks, and slower economic growth were the main reasons for the deregulation in the 1980s. Evanoff et al. (1985) stated that market pressure and existing impetus caused financial deregulation to take place. Krippner (2011) argued that the deregulation in the 1980s was part of political decision making the market, not the politicians responsible for unexpected economic consequences. Hare and Poole (2014) also said less government interference in the economy was part of the government's commitment before the 1980 election.

In the 1980s, the US banking sector was in significant distress, and many factors contributed to this distress, including deregulation, increased competition, and a series of economic shocks. In the mid-1980s, the banking sector's credit crisis occurred through various factors, including risky lending, interest rate volatility, and regulatory failure. Furthermore, throughout the 1970s, the capital level in large US banks started to decline, and in the early 1980s, many Latin American countries defaulted on their debt obligation (Sherman, 2009). All these factors significantly impacted the international banking system and raised concern about the adequacy of bank capital and banks' ability to absorb losses. In the 1980s and early 1990s, over 1500 banks became insolvent and failed, which was the largest number of bank failures in the USA after the great depression.

The US authority recognised the benefits of international coordination to mitigate the crisis of the 1980s and started to work with the international body to set the principles of capital requirements. Then, the committee of G-10 banking authorities, also known as the Basel Committee on Banking Supervision (BCBS), came together and agreed on a general set of guidelines for banks' capital requirements. This regulatory guideline is known as Basel I issued in 1987, and the committee became a global standard setter for banks being formed in 1974 by the central bank governor of G-10 countries. Over the last four decades, the BCBS issued and published all the significant regulatory changes recommended and adopted worldwide. In Basel I, the capital was divided into two tiers: tier 1 and tier 2 capital; tier 1 capital included preferred shares and common stocks, and tier 2 capital included undisclosed reserves, revaluation reserves, loan-loss reserves, subordinated debt and equity-like debt instruments. The capital adequacy was measured with the risk-based capital ratio demonstrating banks' risk portfolio, and the minimum risk-weighted capital it set was eight per cent. Basel I focused on credit risk especially dealing with non-performing loans. Brunnermeier (2009) stated that Basel I increased the demand for securitised and structured products linked with the 2007-2008 financial crisis.

BCBS issued Basel II in 2004, also known as the Revised Capital Framework, as an update to the Basel I framework. It was issued to address some shortcomings of Basel I, which was criticised for being too simple and not taking the complexity of modern banking into account. IBM (2021) stated that Basel II was introduced because of the significant losses in the international market in 1992. The committee recommended the updated approach known as the "three pillars" framework to measure risk. Basel II focused on banks' supervisory framework, market discipline, and minimum capital requirements. The Basel II frameworks' shortfalls were observed during the last financial crisis that started in the USA towards the end of 2007. In response to this crisis, the committee introduced Basel III in 2010, which extended the bar for capital requirement and emphasised the level of liquidity needed to avoid maximum economic shock, leading to a banking crisis. However, following the 2007-2008 crisis, large economies like the USA, UK and EU took tighter regulatory measures to stabilise the sector.

In response to the financial crisis of 2007-2008, the US government passed the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010, also known as Dodd-Frank Act, to make a safer and more stable financial system and to protect customers. This act intended to regulate the financial activities and the sources that led to the financial crisis of 2007-2008. It also aimed to end the 'too big to fail' factor and overhauled the financial system making changes and affecting all federal financial regulatory agencies and the entire financial sector. It created new agencies, including the Consumer Financial Protection Bureau (CFPB), Financial Stability Oversight Council and the Office of Financial Research, and Overly Liquidation Authority and assigned more responsibilities to the existing agencies. Then the Volcker Rule of this act abstained financial institutions from making speculative lending and investments. This act enabled the Financial Stability Oversight Council and Orderly Liquidation Authority to monitor financial stability and restructure or liquidate financial institutions via Orderly Liquidation Fund. The council was also authorised to break up large banks and force banks to increase their reserves if they pose systemic risk. Furthermore, this act enabled CFPB to prevent predatory mortgages and help consumers understand the terms and conditions before signing a mortgage agreement. It requires financial institutions to disclose information in a way that customers can easily understand. However, many critics said this tighter regulation would put American banks and other financial institutions in a disadvantageous position in the global market and might lose in competition. Later in 2018, the Dodd-Frank Act was relaxed with the enactment of the Economic Growth, Regulatory Relief, and Consumer Protection Act.

The UK also took similar action after the 2008-2009 financial crisis. The UK government formed a commission in 2010 named Independent Commission on Banking, chaired by John Vickers, to look at the structural and relevant non-structural reforms to the country's banking sector. This committee was formed to make recommendations to reform the banking sector, reduce systemic risk and likelihood of bank failure, and mitigate banks' moral hazard. The commission was also asked to focus on the market competition. The commission published its report, known as the Vickers report, in April 2011, and the UK government agreed with most of the recommendations made by the commission and turned it into a new baking act. The act enabled HM Treasury and Prudential Regulation Authority (PRU) to implement the recommendations of the Vicars report. The major reforms made by this act included a ring-fencing requirement for banks, the introduction of senior managers and a certification regime, the payment system regulators, the criminal offence of reckless misconduct in the management of a bank, the bail-in stabilisation for the special resolution regime and the cap on the cost of payday loans. The ring-fencing reform separated the core banking service from wholesale and investment banking activities. It reduced the implicit government guarantee from the presumption that when the banks are at risk of failure, the government will step in and bailout. It made deposits as preferential debt; as a result, if a bank becomes insolvent, the depositors will get preference in the insolvency hierarchy. This reform was made intending to contain the contagious risk. Banks are also required to maintain sufficient primary loss-absorbing capacity comprising regulatory capital and debt instruments that can bear losses when a bank fails. This act gave the Prudential Regulation Authority, Financial Conduct Authority, and Bank of England more responsibilities and executive power to stabilise the financial sector. This act made banks' senior managers responsible for breaching rules that fall in their areas of responsibility. It also criminalised financial misconduct by senior managers. The capital requirement for ring-fencing banks is higher than the Basel III minimum standard (HM Treasury 2018).

Furthermore, in 2012 the European Union created a banking supervision and resolution system called Banking Union in response to the crisis. The Baking Union also focused on controlling big banks and bailouts like their UK and USA counterparts. It introduced two key regulatory mechanisms, Single Supervisory Mechanism (SSM) and Single Resolution Mechanism (SRM). The SSM focused on managing the large and important banks and banking groups in the EU, and it set specific criteria to select these intermediaries, including their size, cross-border activities, economic importance, and reliance on public support. Then, the SRM was introduced, intending to minimise the financial and economic cost of bank failure. They formed a Single Resolution Board that will decide on banks' resolutions cooperating with national resolution authorities as an independent EU agency. The Banking Union also introduced Single Fund that will be used if shareholder and creditors' contributions are insufficient prior to resolution. It put the creditors and shareholders first to bear the losses rather than the state fund. It also implemented a prudential capital act and deposit insurance scheme (European Parliament, 2023).

The BCBS first described banks' liquidity risk in 1997, and they explained some possible reasons for this liquidity risk. Basel II redefined the capital requirement, emphasised banking supervision and market discipline, and defined liquidity risk under the supervisory framework. Then, in Basel III, banks' minimum capital requirement included a minimum Capital Conservation Buffer Ratio and a minimum Common Equity Tier 1 (CET1) capital ratio. Then the liquidity ratio needed is defined explicitly and classified into two stages – i) liquidity coverage ratio (LCR) and ii) Net Stable Funding ratio (NSFR). The LCR is the high-quality liquid assets to meet liquidity demand for one month in stressed economic conditions, and NSFR is to meet liquidity demand for one year.

Basel III regulatory changes were made in the wake of the 2007-2008 financial crisis, and it is seen as a "best practice" regulatory standard across the member countries as they are obliged to adopt and implement the recommended changes. Beck, Jones, and Knaack (2019) stated that many non-member developing countries feel implicit pressure and are obliged to adopt Basel III standards even if the changes do not fit their needs. According to the Financial Stability Institute, until 2019, around 81 non-member jurisdictions have taken steps to implement a minimum of one component of Basel III. Beck, Jones, and Knaack (2019) later stated that the reasons why developing economies adopt international standards are signalling to international investors, international expansion facilitating cross-border coordination, peer learning and peer pressure, and technical advice from the International Monetary Fund.

The banks in Bangladesh have been following the Basel regulatory guideline since 1996, and the central bank adopted Basel I and II in 2002 and 2010, respectively. Then, the country started to implement Basel III in 2015. The measure of LCR provided by Bangladesh Bank following Basel III regulation is –

$$LCR = \frac{Stock\ of\ high\ quality\ liquidity\ assets}{Total\ net\ cash\ outflows\ over\ the\ next\ 30\ celender\ days} \geq 100\%$$

The Stock of high-quality assets defined by the central bank are – the cash on hand, balance with the central bank and unencumbered approved securities (excluding lien). All the scheduled banks in Bangladesh must submit their LCR statements monthly and NSFR statements quarterly (Bangladesh Bank, 2014).

The banking institutions in the country are subject to following Basel III regulations. There are 60 banks in the country, including three specialised, six state-owned, nine foreign and 42 private commercial banks (Bangladesh Bank, 2020). Individuals or private entities own most private banks, and some private banks operate as joint ventures of domestic private and foreign-owned institutions. The foreign banks are incorporated in different countries and operate in Bangladesh as branches. Their fundamental operations and activities as deposit-taking institutions are almost the same as their counterparts in developed economies.

On the other hand, along with banking institutions, there are also Non-Bank Financial Institutions (NBFIs) operating in the country. The Financial Stability Board (2017) defined NBFIs as "credit intermediation involving entities and activities outside the regular banking system". The world bank defines non-bank financial institutions as those that do not have a banking license and cannot take public deposits. It included insurance companies, venture capitalists, pawn shops, currency exchanges, and microloan organisations as NBFIs. The NBFIs' services differ from banks, but they work as competitors and are specialised in different areas. In the USA, the NBFIs comprise insurance companies, pension funds, investment companies, hedge funds, private equity firms, venture capital firms, financial companies, money market funds, and real estate trusts. According to the Financial Stability Oversight Council (2022), The NBFIs accounted for approximately 33% of the total financial assets in the USA. Under the Dodd-Frank Act (2010), the NBFIs have been divided into three categories: foreign NBFIs, U.S. NBFIs, and US NBFIs supervised by the Federal Reserve Board of Governors. The key difference between the US NBFIs and 'US NBFIs supervised by the Federal Reserve Board of Governors' is that the board supervise NBFIs based on their size, scope, nature, scale, concentration, interconnectedness, and the mix of activities measuring their level of threat in financial stability in the USA.

Furthermore, the NBFIs play a key role in the UK financial system, but the nature and function of NBFIs in the UK differ slightly from many other countries. The International Monetary Fund categorised NBFIs in the UK into three categories: pension funds, insurance corporations and Other Financial Intermediaries. The other financial intermediaries include hedge funds, other investment funds, Real estate funds, finance companies, broker-dealers, structured finance vehicles, central counterparties, Captive financial institutions and money lenders, and bank holding companies. The overall size of the NBFIs in the UK is marginally below the banks, and they hold a third of corporate loans, a third of corporate bonds, and nearly half of the unsecured consumer loans (International Monetary Fund, 2022). The banking institutions are interlinked with NBFIs by ownership, balance sheets, and activities; as a result, a large part of NBFIs' activities in the UK get prudentially consolidated in banks.

The size and nature of NBFIs in Bangladesh differ from that in developed economies. The NBFIs in Bangladesh include insurance companies, leasing companies, investment companies, merchant banking, assets management companies, microfinance institutions, securities firms, and factoring companies. Over the last ten years, the NBFIs have increased to 15 per cent (Bangladesh Bank, 2020). The NBFIs applied in this study can partly be compared with the non-bank finance companies in the USA and UK that provide different financial services to businesses and individuals. In the USA, these institutions include consumer finance, commercial, leasing, and factoring companies relying on short-term borrowing to fund their lending activities. Their activities include consumer lending, small business lending, leasing, factoring, structured finance, and investment management. According to Federal Reserve, the total assets of non-bank finance companies in the USA is nearly US$ 4.4 trillion. They provide loans to individuals and businesses who may not qualify for traditional bank loans. They also accounted for 17 per cent of the total outstanding debt and 8.5 per cent of the total financial assets in the USA (Financial Stability Oversight Council, 2020). The NBFIs in Bangladesh are also comparable with the non-bank finance companies in the UK, whose general activities are consumer and commercial lending, leasing, factoring, invoice discount, assets bucket lending and bridge finance. According to the Financial Stability Report of England (2020), lending by non-bank finance companies is around 13 per cent of total UK lending. Moreover, the NBFIs in the European Union are fundamentally almost the same as the UK and USA.

There are 34 NBFIs operating in the country, including 15 private domestic, 15 joint ventures, two government-owned NBFIs, and one as the subsidiary of a state-owned commercial bank (Bangladesh Bank, 2020). The NBFIs are also regulated and supervised by Bangladesh Bank, the country's central bank. Bangladesh Bank implemented the Basel II capital requirement within the NBFIs in January 2012, and they are subject to maintaining a minimum of 10 per cent of the risk-weighted capital ratio. Since December 2013, they have been allowed to take a minimum of 3 months term deposits and are subject to maintaining a 5.0 per cent statutory liquidity requirement, including a minimum 2.5 per cent cash reserve ratio on a bi-weekly basis. They also must follow many other prudential regulations and central bank policies like corporate governance (Bangladesh Bank, 2021). NBFIs provide banking services as a close substitute to commercial banks. Their sources of finance are term deposits, credit from banks and other financial institutions' securitisation, Call Money, and bonds. Unlike banking institutions, they are not allowed to issue cheques, pay-order, or demand drafts; they cannot receive demand deposits, and they cannot involve in foreign exchange financing (Bangladesh Banks, 2020). Their operational areas are mainly within diversified financing models like lease financing, private placement of equity, bridge financing, syndicated financing, etcetera; many NBFIs have also been operating in corporate finance. Leasing is the most selling product of NBFIs, and other top-selling products are term lending and house finance. On average, 94 per cent of their lending is from these three loan products. The NBFIs generally operate in the gap left by the banks, but they also compete in the same market with banking institutions.

The BCBS recommended the liquidity ratios, in Basel III, for a stable banking sector but did not clarify the liquidity and liquidity risk. They defined it as "the ability to fund increases in assets and meet obligations as they come due, without incurring unacceptable losses". Greuning and Bratanovic (2003) stated that banks are vulnerable to liquidity risk in two aspects: 1) funding liquidity risk, which is bank-specific and 2) market liquidity risk, which is systemic. Drehmann and Nikolaou (2010) stated that the liquidity risk BCBS addressed is close to funding liquidity risk, and the committee mixed the concept of liquidity and liquidity risk. Drehmann and Nikolaou (2010) defined bank liquidity as the ability to settle obligations with immediacy. They defined it as a binary concept, like whether or not a bank can settle its obligations; it is associated with one particular point in time. On the other hand, funding liquidity risk is the possibility of not being able to settle obligations with immediacy over a specific horizon. It can take infinitive value because it relates to the distribution of future outcomes. Greuning and Bratanovic (2003) also provided a similar definition; they defined liquidity risk as "the risk of a bank's inability to meet its payment obligations as liabilities fall due." Funding liquidity risk is always forward-looking and concerns the future ability to settle obligations. Moreover, the market liquidity risk is the risk of being unable to sell assets in the market on time without offering a discount. The issue with funding liquidity can lead to market liquidity risk as they are correlated, and their downward slope can emerge in crises (Drehmann and Nikolaou, 2010). When the market liquidity risk intensifies, it becomes a liquidity crisis characterised as an acute shortage of liquidity and lack of cash or liquid assets across financial institutions. The demand for liquidity increases, and the supply decreases simultaneously during a liquidity crisis. This study has focused on banks' funding liquidity risk from different perspectives and its impact on the key banking sector variables in Bangladesh in terms of Basel III implementation.

There have been growing arguments and studies for and against this tighter regulation in the banking sector. It has been argued and explained that this Basel III tighter capital requirement might pave the way to increase the growth of shadow banking or NBFIs that are not as strictly regulated as banking institutions (Martinez-Miera and Repullo, 2018; Fahri and Tirole, 2017 and; European Commission, 2012). The NBFIs also play an essential role in the stability of a financial market. The leverage of NBFIs can also be vulnerable to 'run' like banking institutions which can arise from liquidity and maturity transformation and poses contagious risks. They can reinforce procyclicality by enhancing credit supply during a stable period and when confidence surges, but the credit supply can fall rapidly when the confidence is lost (Financial Stability Board, 2017). This risk in non-banking institutions can spill over into the regular banking system and become amplified. The global financial crisis of 2007-2008 showed how the regular banking system was exposed to and interconnected to the risk of non-bank entities.

Furthermore, it is evident in the literature that the regulatory changes in a banking sector affect the bank return and bank cost in the first place (Baker and Wurgler, 2015; Handorf, 2011; Truck, Laub and Rachev, 2004; Fries and Taci, 2004; Pasiouras, Tanna and Zopounidis, 2009). Fries and Taci (2004) regarded the change in bank cost as an indication of the progress of any change made in the banking sector. They further explained that banks' cost efficiency gained over the period changes if it is correlated with the changes in incentives or constraints in banking associated with regulatory changes. Gaining cost efficiency reduces the intermediation cost of turning savings into investments that contribute directly to the entire economy, like productivity gains in other economic sectors (Fries and Taci, 2004). However, the increase in bank cost or decreasing banks' cost efficiency can increase the risk of bank failure in a stressed economic condition, like the increasing risk of bank failure in the USA in the 1990s (Wheelock and Wilson, 2000).

This study aimed to examine the correlation between liquidity risk and bank capital as a pre-step and then estimate their effect on bank return, cost efficiency, and the growth of banks and NBFIs in the country in terms of Basel III implementation. Basel III was introduced to make the financial sector stable and shockproof, and it is made adaptable under the local authorities worldwide. Thus, its impact on bank return, bank cost and the growth of banks and NBFIs will vary in different economies of the world, especially for economic, infrastructure and technological differences. Furthermore, the financial intermediaries of all countries are almost identical, but there is a significant difference in their level of operation and the risk they pose in different economies. Regarding the studies on bank return and bank cost in Bangladesh, Rahman et al. (2018) focused on Basel II implementation and examined the impact of capital requirements on the cost of financial intermediation and banks' risk-taking behaviour. They took two different ratios of 'Net Interest Margin' as the measures of banks' intermediation cost and equated bank risk with 'Return on Assets' and 'Capital Ratio' with z scores. Zheng et al. (2017) further conducted an almost similar study based on bank-level data from 2000 to 2015. Lee and Hsieh (2013) also included Bangladesh when they conducted a study examining the impact of capital adequacy on bank profit in 42 Asian countries based on data from 1994 to 2008. Furthermore, in terms of cost efficiency, most of the studies in the literature have been conducted based on the transition period of different European countries and banks' ownership structures (Nikiel and Opiela, 2002; Kraft and Tirtiroglu, 1998; Hasan and Marton, 2003; Grigorian and Manole, 2002; Fries and Taci, 2004). Additionally, Andrle et al. (2019) investigated the macroeconomic cost of implementing Basel III in nine European economies. Moreover, there have been some studies that examined the impact of Basel III regulation on the growth of different financial intermediaries, especially banks, insurance and NBFIs, but they have mostly been conducted based on the USA and European economies following different types of data and methodological approaches (Martinez-Miera and Repullo, 2018; Fahri and Tirole, 2017; Financial Stability Board, 2017; Irani, Iyer, Meisenzahl and Peydro, 2018). The results of all the studies mentioned are not identical. Moreover, very little attention has been given to indicating banks' explicit and implicit costs of implementing Basel III in different economies worldwide. The BCBS (2019) also mentioned this gap when they examined bank capital's impact on banks' crisis probability. However, no empirical study has been conducted yet examining the impact of liquidity risk and bank capital on bank return, bank cost and the growth of banks and NBFIs in terms of Basel III implementation in Bangladesh.

As the key regulatory changes in Basel III are the changes in liquidity risk and bank capital, this study has set the following objectives –

It starts by looking at how the bank capital determines the liquidity risk (as a pre-step)

How far has Basel III regulation affected the key banking sector variables in Bangladesh?

Then this study investigated the following objectives in terms of Basel III implementation in the country.

1. Effect of liquidity risk and bank capital on Bank return
2. Examining banks' cost efficiency and the effect of liquidity risk and bank capital on cost efficiency
3. Effect of the liquidity risk and bank capital on the growth of banks and NBFIs

The following sub-questions have been developed for this study –

Q0: How does the bank capital determine the liquidity risk?

Q1a: What is the effect of liquidity risk on bank return?

Q1b: What is the effect of bank capital on bank return?

Q2a: How far cost-efficient are banks?

Q2b: What is the effect of liquidity risk on cost efficiency?

Q2c: What is the effect of bank capital on cost efficiency?

Q3a: What are the effects of liquidity risk and bank capital on the growth of banks?

Q3b: What are the differential effects of bank liquidity and regulatory capital on the growth of NBFIs?

This study has broadened the current literature in numerous aspects. Unlike any other study, this study has applied four different measures of banks' liquidity risk and examined how they are correlated with bank capital. This study has also shown that a consistent and unbiased cost efficiency result can be derived through a comparative study of several Stochastic Frontier Analysis (SFA) models with bank-level panel data. Furthermore, both one-step and two-steps approaches have been found in the literature for examining banks' cost efficiency and their determinants (Altunbas et al., 2007; Fries and Taci, 2004; Mamonov and Vernikov, 2017; Lin, Doan and Doong, 2015), but no study has applied the justified cost efficiency estimation at the second stage for examining the determinants like this study.

The key findings of this study are the correlation between bank liquidity and bank capital, determinants of bank return, banks' cost efficiency, and the growth of banks and NBFIs in Bangladesh in terms of Basel III implementation. This study has also shown the parameters of the cost frontier, measures of banks' cost efficiencies which is the distance from the frontier. Furthermore, the year fixed effect results have shown the difference in bank return, bank cost, and the growth in banks and

NBFIs after implementing Basel III, indicating this new regulation's impact. These findings and the applied method have added to the knowledge and limited literature. It will also provide the country's regulators with significant insight, demonstrating the implicit and explicit cost of implementing Basel III.

2. Literature review

This chapter has explored relevant literature that focuses on the correlation between liquidity risk and bank capital and the effect of these key variables on bank return, cost efficiency and the growth of banks and NBFIs.

Bank liquidity plays a vital role in the stability of a banking system, and any instability directly affects bank return, banks' cost efficiency, and their growth. Any instability in the banking sector tends to lead to a crisis, which intensifies in many ways. A crisis tends to lead the banking sector to confront a 'bank run'. During a bank run, depositors expect the banks to fail and rush to withdraw their deposits (Diamond and Dybvig, 1983). This sudden withdrawal leads the banks to liquidate their assets at a loss which leads to lower bank returns, and in an intense situation, it might lead to bank failure. Diamond and Dybvig (1983) stated that the fear of bank failure reduces the production in an economy by disrupting the monetary system. Liquidity risk is also correlated with a 'systemic banking crisis.' Laeven and Valencia (2008) identified 124 'systemic banking crises' from 1970 to 2007, and the crisis years were found to coincide with deposit runs or the introduction of a deposit freeze or bank intervention or extensive liquidity support. The banking sector has a high gross fiscal cost for this systemic crisis which ultimately affects the bank return and banks' lending activities. When there is a systemic crisis, the regulators generally take emergency measures to contain the crisis. Consequently, the economies confront long-run challenges, which entail rebuilding banks' balance sheets and resuming regular functioning credit and legal systems (Laeven and Valencia, 2008).

Managing liquidity risk has been defined as the primary source of banks' vulnerability, and Diamond and Dybvig (1983) emphasised deposit insurance to protect public safety. Furthermore, bank capital is considered one of the most important regulatory instruments, and there are arguments against and for increasing this regulatory bank capital. Its effect has been examined in the literature on numerous key banking sector variables.

Bank capital and the liquidity risk

Regarding the correlation between bank capital and liquidity risk, two different hypotheses are widely seen in the literature: the 'Financial fragility or crowding-out hypothesis and the 'risk absorption' hypothesis.

Referring to the New Keynesian economists, Schroeder (2021) defined financial fragility as a state in which a shock can trigger financial instability. The New Keynesian analyses further characterised financial fragility as a high probability of default and low bank profitability (Aspachs et al., 2007). Financial fragility is also recognised in Hyman Minsky's financial instability hypothesis (Minsky, 1975);

he explained that the fragility lies in the relationship between the profit generated by assets and the payment commitments on liabilities. The fragility in the banking sector remains mainly in the liquidity risk.

The financial fragility hypothesis explains that increasing bank capital decreases banks' liquidity creation (Berger and Bouwman, 2009). Liquidity creation is measured by equating different weighted liquid assets and liabilities together and then turned into a ratio with total assets. By increasing liquidity creation, banks can increase their fund and liquid assets and help them to meet obligations without incurring additional losses, which, they said, complies with BCBS's definition of bank liquidity. Here the liquidity risk lies in how the banks invest this fund and mitigate the risks. The key difference between the liquidity creation and the measures applied in this study is that the liquidity creation weighted and equated all the liquid assets together and turned them into a single ratio, but this study has applied different liquid and illiquid assets ratios separately as the measures of liquidity risk showing the liquidity risk in detail. Distinguin, Roulet and Tarazi (2013) implied that the increase in liquidity creation decreases banks' liquidity risk. The financial fragility hypothesis explains that banks raise funds by collecting deposits from depositors, and they lend them to borrowers by creating loan products. This process gives banks an advantage in assessing lending profitability by monitoring the loans and gaining private information. This advantage raises an agency issue; the banks might extract rents from depositors by requiring a greater share of the loan income. The banks might stop the monitoring process if the depositors refuse to pay this higher cost. In this case, the depositors become reluctant to deposit their money in the banks as they know that the banks might abuse their trust. As a result, the banks must gain depositors' confidence by taking a fragile financial policy with a large share of deposits (Distinguin, Roulet and Tarazi, 2013). Financial fragility allows the banks to increase deposits and lend to borrowers through more liquidity creation. On the contrary, it has been argued that the primary reason for having bank capital is to adjust risks, including the risk of a bank run, liquidity crunches, credit risk and many other risks (Berger and Bouwman, 2009). This hypothesis explained that a higher bank capital tends to mitigate this financial fragility and increase banks' bargaining power. Thus, according to this hypothesis, a higher capital tends to decrease banks' liquidity creation. Gorton and Winton (2000) further stated that a higher capital could decrease bank liquidity through "crowding-out of deposits". They explained that an increase in bank capital shifts investors' funds from liquid deposits to relatively illiquid bank capital, so a capital increase could decrease bank liquidity and increase liquidity risk.

On the other hand, the 'risk absorption' hypothesis explains the following. The increase in bank capital increases bank liquidity. Allen and Gale (2004) argued that banks are exposed to higher liquidity risk when they increase liquidity because it could lead to a liquidity crisis during a financial shock or bank run. The increase in bank capital allows banks to mitigate this risk.

Many studies in the literature focused on banks' liquidity position to investigate the correlation with bank capital, and they applied the measure of liquidity creation, which is a combined equation of differently weighted liquid assets and liabilities (Distinguin, Roulet and Tarazi, 2013; Berger and Bouwman, 2009; Duqi and Al-Tamimi, 2018; Ghosh, 2016). The correlation between bank capital and liquidity risk is inconsistent across the literature. Distinguin, Roulet and Tarazi (2013) examined the correlation between bank capital and banks' liquidity creation. They used a simultaneous equation framework to represent bank liquidity, indicating the overall liquidity position of banks where they implied that the higher the liquidity creation, the lower the liquidity risk. Based on the EU and USA bank-level data, they found that banks' liquidity creation and regulatory capital are negatively related. Ghosh (2016) also found a similar result, but he applied a different measure of bank capital. Using the US commercial bank data from 1993 to 2003, Berger and Bouwman (2009) found that banks' liquidity creation is positively related to the price-earnings ratio, suggesting that the higher the banks create liquidity, the higher they are valued by their investors. They have shown that large banks are positively related when it includes off-balance sheet activities, and it is not significantly related when it takes only on-balance sheet activities; the relationship is negative for small banks. However, the risk proportion has not been addressed in their study.

2.1 Impact of liquidity risk and bank capital on bank return

2.1.1 Liquidity risk and bank return

It is theoretically well-recognised that two key activities, liquidity creation and risk transformation, are the reasons why banks exist (Berger and Bouwman, 2009). Banks play the intermediation role of transforming deposits, which are banks' liabilities, into illiquid assets (Athanasoglou et al., 2008; Bonfim and Kim, 2012). Banks' most funds are liabilities, including demand deposits, and they use a small part of the equity to grant loans (Diamond and Dybvig, 1983). When a bank receives a deposit from depositors, a liability is created in the balance sheet, and it turns into an asset by lending it to the borrowers (Hartlage, 2012). A bank must manage the assets and liabilities sites to meet depositors' withdrawals without incurring any additional cost. Banks, therefore, are exposed to the risk of insufficient liquid assets to meet demand from depositors (Gatev et al., 2007). If some liabilities invested are claimed back with short notice, a bank may face the cost of higher liquidity risk. When a bank confronts a liquidity shortage, it sells its assets. It can cause that asset price to fall and lead to a market liquidity risk in an extreme economic condition, as it puts the other banks under stress to sell that asset as well (Demirgüç-Kunt and Huizinga, 1999; Shen et al., 2001). Banks with high liquidity risk are more likely to have the cost of it, which directly impacts their return. Moreover, the impact of liquidity risk on bank return is complex, as the higher the liquidity ratio, the lower the liquidity risk, and a higher liquidity ratio can lead to lower interest margins and lower returns (Demirgüç-Kunt et al., 2003; Naceur and Kandil, 2009), and the shortage of liquidity leads to selling assets probably at a lower rate, borrowing fund from the money market or by increasing the interest rate on different deposits. All of them cost banks and affect their return. Handorf (2011) argued that Basel III required bank liquidity would affect bank return by increasing bank costs by the term structure of interest rates, which vary with their maturity. Truck, Laub and Rachev (2004) also stated that banks' cost of liquidity might increase if there is an increase in maturity gap or maturity mismatch.

The effect of liquidity risk on bank return is mixed in the literature. One of the primary sources of bank profit is the banks' net interest margin. Many studies focused on banks' net interest margins to examine the effect of banks' liquidity risk, and they have found that banks with lower liquidity risk have lower interest margins (Demirgüç Kunt and Huizinga, 1999; Shen et al., 2001; Demirgüç-Kunt et al., 2003; Naceur and Kandil, 2009). Based on the data of 17 Dutch banks, Bonner (2015) has shown that increasing regulatory liquidity increases banks' investment in government bonds and decreases lending to customers indicating lower interest margins. Vazquez and Federico (2015) explained that banks with higher leverage and weaker liquidity structure are more likely to fail after a crisis. Furthermore, relying on the wholesale market to maintain liquidity risk have a negative effect on banks' performance and price in the stock market (Raddatz, 2010; Demirguc-Kunt and Huizinga, 2010). Bordeleau and Graham (2010) found that an increase in liquid assets decreases the probability of banks' liquidity crisis and default risk in a market, but it affects bank return.

2.1.2 Capital ratio and bank return

According to conventional wisdom in banking, a higher capital ratio decreases banks' profitability (Staikouras and Wood, 2004). It has been explained that the increase in capital ratio tends to decrease the risk of equity which lowers the equilibrium of return on equity expected by investors. Banks also confront the tax exemption loss arising from increased capital ratio. Most studies have focused on the determinants of bank return or profit and used bank capital as one of the determinants. The capital ratio has also been used as a proxy for bank regulation as the market would equalise capital ratios for banks of the magnitude (Bourke, 1989). It has also been explained in the literature that bank capital is positively related, and the following reasons have been given why it may be positively related to bank return or bank profit (Berger, 1995). The increase in bank capital may increase bank return because it reduces the cost of financial distress like bankruptcy. They also can be positively related because retained earnings may have increased the capital ratio. If the bank capital is increased to expand into a profitable product line or reduce risk-related barriers, they can be positively related. Banks with a higher capital ratio may also be able to increase funds easily and can increase revenue by lending them after turning them into loan products. The better-capitalised banks may also be able to avoid issuing off-balance-sheet guarantees like standby letters of credit and loan commitments.

The correlation between bank return and bank capital is mixed in the literature, and the studies have been conducted based on the bank-level data of different countries following different empirical approaches. Staikouras and Wood (2004) Examined the internal and external factors that affect the return of EU banks. Applying OLS and the fixed effect models with the data from 1994 to 1998, they have found that bank capital is positively related to bank return. Kohlscheen, Murcia and Contreras (2018) also found a similar result when they examined the determinants of bank profitability based on the balance sheet data of 19 emerging economies' 534 banks. They examined the determinants in terms of bank credit and risk premia. Applying the System GMM, they have found that higher long-term interest rates increase bank profitability, but higher short-term interest rates decrease the profitability, and they explained it is because of the increase in funding costs. They applied the capital ratio as a control variable. However, using the bank-level data from 2003 to 2009 and applying the System GMM, Tan and Floros (2017) have shown that bank capital is negatively related to bank profitability. Moreover, using a quarterly financial report and stock market data of the six largest Canadian banks from 1982 to 2010, Guidara et al. (2013) have found that bank return is not related to bank capital. All the studies mentioned applied Return on Assets (ROA) as the main measure of bank profit or profitability, and few of them applied Return on Equity (ROE) and Net Interest Margin (NIM) as a second or supporting measure of bank return or bank profitability.

2.2 Impact of liquidity risk and bank capital on cost efficiency

2.2.1 Liquidity risk and cost efficiency

It has been explained above how liquidity risk can affect the bank cost, ultimately affecting the bank return. This study has estimated banks' cost efficiency and examined the effect of liquidity risk on cost efficiency separately.

Basel III was introduced in 2010, and the countries started adopting it since 2012, so limited studies have focused on the correlation between liquidity risk and banks' explicit cost. Following a two-step approach and based on the data of Kosovo's commercial banks, Ahmeti et al. (2022) have shown that cost efficiency is positively related to banks' liquidity risk. They estimated the cost efficiency with Data Envelopment Analysis (DEA) in the first step and then applied the estimated cost efficiency in the second step along with other control variables. The measure of liquidity risk they applied is the ratio of total loan to deposit and short-term funding, and they used the fixed effect model in the second step. Following a similar approach, Amin et al. (2018) have shown a similar result based on the bank-level data of OIC countries. However, Sakouvogui and Shaik (2020) have found that bank liquidity and solvency are negatively related to banks' cost efficiency in the USA's commercial and domestic banks.

Baltas et al. (2017) investigated the impact of liquidity creation on banks' cost efficiency. They have also followed a two-step approach like this study, where they estimated the cost efficiency through SFA and examined the impact using a Vector Auto regression (VAR) model. They calculated the liquidity creation by weighing different liquid and semi-liquid assets, liquid and semi-liquid liabilities and financial guarantees. They also termed it as banks' liquidity risk. Their data was an unbalanced panel of all financial institutions in the UK and Greece that provide credit. They have shown that liquidity creation and banks' cost efficiency are positively related, which means decreasing liquidity risk increases banks' cost efficiency. Altunbas et al. (2007) examined the cost efficiency and focused on bank risk, and they controlled the 'net loan to asset' ratio as a measure of liquidity risk.

2.2.2 Bank capital and cost efficiency

In Basel III, banks' risk-based capital ratio has been supplemented by a non-risk weighted leverage ratio and bank liquidity. The BCBS (2019) revealed that the higher capital ratio reduces the probability of a banking crisis, but they stated it is a drag on loan growth. Baker and Wurgler (2015) stated that this tighter capital requirement would increase banks' cost of capital via the low-risk anomaly as it has neglected banks' private costs. Additionally, according to the capital structure theory, deposit and debt finance are less expensive than equity finance, and a percentage increase in equity finance would increase banks' Weighted Average Cost of Capital (WACC). The BCBS (2019) also mentioned the tax exemption loss for banks, which firms typically enjoy by having debt finance.

Most studies in the literature have focused on the impact of equity ratio on the crisis probability and banks' risk-taking behaviour (Bordo et al., 2001; Homolle, 2004; Agoraki, Delis and Pasiouras, 2011; Jokipii and Milne, 2011; Leaven and Levine, 2009; Guidara et al., 2013; BCBS, 2019). Besides, in terms of examining banks' cost efficiency, most studies focused on banks' ownership structure, and some studies applied bank equity as a control variable (Altunbas et al., 2007; Fries and Taci, 2004; Lin, Doan and Doong, 2015; Lu et al., 2018; Mamonov and Vernikov, 2017). The impact of bank capital on cost efficiency is found mixed in the literature. Altunbas et al. (2007); Fries and Taci (2004); and Lin, Doan and Doong (2015) found the capital ratio negatively related, whereas Lu et al. (2018) and Mamonov and Vernikov (2017) found the capital ratio positively related to banks' cost efficiency. All these studies have followed one- and two-step approaches and applied different measures of bank capital. These studies on cost efficiency have been conducted based on single and multiple countries, and they mostly compared the cost efficiency of different ownership structures within the county and comparison of sample countries.

In terms of the impact of bank capital on banks' crisis probability, the BCBS (2019) have shown that when banks' capital ratio increases from 7 to 8 per cent, the crisis probability of banks reduces by 1.6 per cent, and when the capital ratio increases from 12 to 13 per cent, the crisis probability decreases by 0.2 per cent. They measured the probability of crisis as a function of banking system capital per assets and controls where the controls include credit/GDP, bank liquidity, volatility index, house price and trade balance. Bordo et al. (2001) and Reinhart and Rogoff (2008) also showed similar results on the probability of banking crisis and capital ratio. This study has not focused on the crisis probability measures of banks, but it has shed light on the explicit cost of banks, which arises from banks' input prices and outputs. However, Wheelock and Wilson (2000) have shown that the increase in bank costs increased the risk of bank failure in the 1990s in the USA.

2.3 Impact of liquidity risk and bank capital on the growth of banks and differential impact on NBFIs

2.3.1 Liquidity risk and the growth of banks and NBFIs

There is a growing argument in the literature that tighter regulation in the banking sector will facilitate the growth of shadow banking institutions or NBFIs in an economy. The growth of NBFIs would increase the fragility of a market as they can easily spill over into the regular banking system. The European Commission (2012) stated that NBFIs could affect the financial stability of an economy through two types of liquidity risk– market and funding liquidity risk. They explained it as a major source of risk to financial stability, as an illiquid market is likely to affect most institutions. Selling an asset in an illiquid market may decrease the price of that asset, and it will likely affect the balance sheet of all holders of that asset. This problem intensifies if other holders of the same asset seek to sell it. On the other hand, funding liquidity is the ability to raise cash to meet an individual institution's financial obligation. King and Maier (2009) explained funding illiquidity as a real risk of NBFIs' growth; they can be declared bankrupt if they fail to meet margin calls. They further stated that financial institutions could be bankrupted because of funding illiquidity rather than insolvency.

In Basel I and II, the key focus was on bank capital and other supervisory aspects, and in Basel III, the liquidity requirement has been explained explicitly. Therefore, in the literature, bank liquidity has mostly been used to examine the determinants of bank lending or credit risk and has been used as a control variable (Alper, Hulagu, and Keles, 2012). The studies largely applied the assets and liabilities ratio to control the effect of bank liquidity and as a control of funding for bank lending (Cornett, et al., 2011; Gambacorta and Mistrulli, 2004; Berrospide and Edge, 2010; Bridges et al., 2014; Allen and Paligovora, 2015).

2.3.2 Bank Capital and the growth of banks and NBFIs

The third objective of this study has focused on the lending growth of banks and NBFIs as the financial institutions grow by increasing their lending activities or credit supply. Buchak et al. (2018) showed that the regulatory difference between traditional banks and NBFIs is one of the key forces for the growth of NBFIs. They have shown that the regulatory constraints of banks contribute to nearly 60 per cent of shadow banks' growth in the USA. They further stated that the tighter capital requirement is a regulatory burden for the banks and determinants of NBFIs' growth. Irani et al. (2018) further hypothesised that tighter regulation in the banking system might increase fragility in the overall financial system by pushing the intermediation into unregulated or comparatively less-regulated entities. Martinez Miera and Repullo (2019) supported this argument by explaining that increasing capital requirements can shift financial institutions' lending. This shift may occur by leading entrepreneurs to move from bank finance to unregulated or comparatively less regulated finance of shadow banking. It may result in a rise in the default probability of businesses, making the financial system riskier unintendedly.

As Basel III was issued in 2010, the countries following Basel regulation adopted this in different years after 2010. Thus, a limited number of studies are seen in the literature examining the differential effect of Basel III key changes on the growth of different financial institutions in different economies worldwide. However, some studies examined banks' lending growth determinants and focused on liquidity risk and capital ratio. Studies on finding the link between bank capital and the growth in bank lending started in the early 1990s when Basel I was first issued and implemented in 1988.

A few studies investigated the impact of regulatory changes on the growth of banks and NBFIs. Irani et al. (2018) examined the impact of banks' regulatory capital on the rise of shadow banking in the USA, and they focused on loan sales and activities in the secondary loan market. They have found that the undercapitalised banks have reallocated their loans to NBFIs, and bank capital is negatively related to loan sales during market-wide uncertainty. Then they explained that the existence of non-banks in the system affected banks' decision to get around the capital requirements correlated with corporate loans. Buchak et al. (2008) have also shown an almost similar result, but they conducted their study based on the residential mortgage market in the USA. Shadow banks, or NBFIs, experienced sharp growth in their market share from 2007 to 2015, and the regulatory difference between banks and NBFIs in the country is one of two key contributors. They have found that the increase in banks' capital requirement decreases banks' and increases NBFIs' loan share in the residential mortgage market.

Bernanke and Lown (1991) found that banks' lending growth was positively related to banks' initial capital ratio with their set model. Using the bank-level data of the USA from 1979 to 1992, Berger and Udell (1994) have shown that banks reallocated their credit from loans to securities. In the 2000s, several studies found in the literature that focused on the correlation between bank capital and bank lending, which primarily focused on banks' credit risk (Kishan and Opiela, 2000; Berrospide and Edge, 2010; Carlson, Shan, and Warusawitharana, 2013; Beatty and Liao, 2011; Bridges et al., 2014; Kosak, Li, Loncarski, and Marinc, 2015). These studies applied banks' risk-based capital and leverage ratios, and their methods are not identical. All these studies have provided mixed results, probably because of the difference in bank capital types, empirical approaches, and different economies (countries).

3. Variables

This chapter has explained measures of the key variables and then detailed the control variables.

3.1 Measure of liquidity risk and bank capital

3.1.1 Liquidity risk

Banks' liquidity risk is a complex measure, and it can be measured from different perspectives. Drehmann and Nikolaou (2009) stated that there is no consensus on any single measure of liquidity risk. It has been mentioned earlier that many studies in the literature applied liquid creation for measuring banks' liquidity risk, but this study has applied four different measures of liquidity risk instead of simultaneous calculation of different weighted liquid assets and turning them into a single ratio like liquidity creation.

In the literature, different ratios have been used as banks' liquidity measures, and their risk has also been defined based on the existing circumstances. These measures include the liquid asset to total asset ratio (Bourke, 1989; Molyneux and Thornton, 1992; Barth et al., 2003; Demirgüç-Kunt et al., 2003), liquid assets to deposits ratio (Shen et al., 2001) and the liquid asset to the customer and short-term funding ratio (Kosmidou et al., 2005). Here, the higher the ratios, the lower the liquidity risk is and the less vulnerable to the cost of liquidity risk. Furthermore, some other measures are – 'Loan to asset ratio' (Demirgüç-Kunt and Huizinga, 1999; Athanasoglou et al., 2008) 'Net loans to customer and short-term funding ratio' to assess banks' liquidity risk (Pasiouras and Kosmidou, 2007; Kosmidou, 2008; Naceur and Kandil, 2009); here higher ratio indicates banks having higher illiquid assets and poses a higher risk of bank liquidity. For a more precise measure of bank liquidity, Saunders and Cornett (2006) described the 'finance gap or FGAP', which is the difference between total customer deposits and bank loans where a higher ratio implies banks hold more liquidity and are less vulnerable to liquidity risk. This measure is consistent with the Basel III liquidity measure, as the banks can use this cash instantly without incurring any additional cost.

This study has used FGAP, Net loans to customers and short-term funding ratio, liquid assets to total assets ratio and Loan to Assets ratio separately as the measures of liquidity risk to examine the correlation with bank capital and other factors. The liquidity risks have been measured with the balance sheet data, and the measures that have not been applied are homogeneous to the ones applied in this study. The explanation of the liquidity risk measures applied is given below.

FGAP – The FGAP, which is the difference between customer deposits and net loans, has been applied here following Saunders and Cornett (2006). It is a liability for banks, but they are considered banks' liquid assets because they can be withdrawn instantly without incurring any additional cost. A large share of this FGAP or liabilities is considered stable liquidity because they are expected to stay within the banks. Gatev and Strahan (2006) also supported this measure explaining that retail liabilities are more stable than wholesale funds. Here, the FGAP have been standardised by dividing it by an individual bank's total assets and turning it into a ratio. If the gap is significantly high or the ratio is significantly low, the banks must sell their assets and use their cash or external funds to reduce this gap, which could lead a bank to fund liquidity risk and incur additional costs.

Net Loan to customer and short-term funding ratio (NETL/C&SF) – This ratio has been developed following Pasiouras and Kosmidou (2007); it shows the level of illiquid assets compared to stable funding sources indicating the level of liquidity risk a bank poses. The net loan is a bank's illiquid assets, so the higher the ratio, the higher the liquidity risk is.

Liquid assets to total assets (LA/TA) – This ratio has been developed following the literature (Bourke, 1989; Molyneux and Thornton, 1992; Barth et al., 2003; Demirgüç-Kunt et al., 2003). The liquid assets of banks are cash, securities issued by the government or reserve repo, and balances with the central bank and other banks. The liquidity ratio provides information about the shock absorption capability of banks (Vodova, 2013). The market liquidity risk is the same for all banks, but for individual banks, the higher the ratio, the lower the liquidity risk and the higher risk absorbing capability banks have.

Net loan to total assets ratio (NL/TA): Net loan to assets ratio is used as a liquidity risk measure in many studies (Nicolò and Loukoianova, 2007; Kumbirai and Webb, 2010). It shows banks' illiquid assets in terms of total assets, and in this ratio, the higher the share of the loan in assets, the less liquid the banks are.

3.1.2 Bank capital

The measure and definition of capital ratio are found in different units in the literature. BCBS (2010) used the tangible common equity (TCE) ratio to examine the impact of bank capital. TCE is generally calculated by subtracting the intangible assets, goodwill, and preferred stock from the total equity. Another unit of capital mostly used in the literature is Tier 1 capital, which also includes common equity. The central bank in Bangladesh included the following monetary units in Tier 1 capital –

i) Paid up capital
ii) Non-repayable capital share premium account
iii) Statutory reserve
iv) General reserve
v) Retained earning
vi) Dividend equalisation reserve

vii) Minority interest in subsidiaries

(Bangladesh Bank, 2020)

Furthermore, in terms of assets, studies used risk-weighted assets and total assets. In Basel III, the committee introduced banks' leverage ratio, and the measure recommended is –

$$Leverage\ ratio = \frac{Captal\ Measure}{Exposure\ measure}$$

Basel III recommended the Tier 1 capital as a unit of bank capital and the accounting value of exposure which is banks' non-risk weighted assets or total assets, to calculate the leverage ratio (BCBS, 2014). The minimum required leverage ratio the committee recommended is 3 per cent. Tier 1 capital is a bank's core equity, showing its financial strengths to absorb a financial shock. Thus, the higher the ratio, the more stable the banks are.

Basel III introduced the leverage ratio along with banks' risk-weighted assets. It has been mentioned above that the measure of capital and assets ratios are different across the studies, for instance – Common Equity Tier 1 capital and Tangible Common Equity or Tier 1; Base II and III measures of risk-weighted assets. BCBS (2019) stated that the results of different capital ratios are not comparable, and a full standardisation of different estimates across the studies is not possible.

However, for the measure of capital ratio, the literature tends to apply leverage ratio, which is the measure of Tier 1 capital to non-risk weighted assets or total assets (Brooke et al., 2015; Barth and Miller, 2018; Almenberg et al., 2017; BCBS, 2019; Vazquez and Federico, 2015; Beltratti and Stultz, 2012; Mayes and Stremmel, 2014). BCBS (2019) also applied leverage ratio to estimate long-term economic impact. In addition, Acharya et al. (2014) have shown that when the capital ratio is measured with risk-weighted assets, the results are very different from banks' V-Lab stress test, but when measured with total assets, the results are pretty similar. Thus, following the literature and Basel III recommendation, this study has applied the leverage ratio as a measure of bank capital which is banks' Tier 1 capital (the numerator) divided by total assets (the denominator).

3.2 Measure of the explained variables

3.2.1 Bank return

Petersen and Schoeman (2008) stated that the main sources of bank profits are transaction fees on financial services and interest spread on resources, and the Return on Assets (ROA) provide information about the profits generated by every unit of assets.

Most studies in the literature applied ROA as the main measure of bank return and Return on Equity (ROE) as the supporting measure, but they also termed them as bank profit and profitability (Staikouras and Wood 2004; Kohlscheen, Murcia and Contreras, 2018; Tan and Floros, 2017; Guidara et al., 2013). Golin (2001) explained that the ROA shows how profitable the banks are in terms of their asset. On the other hand, the ROE is the second and a supportive measure of bank return, as ROE may vary depending on managers' decisions. Thus, following the literature, this study has applied ROA as the main measure and ROE as the supporting measure of bank return.

3.2.2 Cost efficiency

This study has followed the SFA approach to estimate banks' cost efficiency, which follows the production function. The cost efficiency is measured with the unit of outputs for a given level of input prices. Goods and services produced by banks require a technical production function combining inputs and some transformation process to bring that goods and services into existence (Sealey and Lindley, 1977). All banks go through the same process irrespective of the standard of goods and services. Sealey and Lindley (1977) provided an analogy to relate the production function of banks and other industries: "Logs lying in the forest are not the same things as logs at the sawmill. The process of hauling the logs to the river, floating them down, and getting them to the sawmill is just as much production in the technical sense of the word as the business of felling the trees and stripping the bark off the stems." They made this example analogous to the production of financial institutions, where the financial institutions process the funds into loans.

Total cost and outputs – The variables selected to estimate the cost efficiency across the literature are slightly different; most studies used banks' interest and operating costs as total costs. However, there are arguments over 'Customer Deposit' as banks' output. Sealey and Lindley (1977) argued that the deposits are inputs based on the asset-based approach. On the other hand, based on banks' value-added approach, Berger, Hanweck and Humphrey (1987) treated the deposits as banks' output. However, Banks generally retain a certain percentage of customer deposits and turn the rest into different loan products, so a higher customer deposit means a higher loan. Thus, there is significantly high multicollinearity between loans and customer deposits; this problem has also been found in the sample data of this study. Therefore, banks' loans and securities have been treated here as outputs following the asset-based approach. Furthermore, the intermediation approach has been followed here to define banks' total cost, which assumes that efficient financial institutions would minimise their operating cost and interest expenses for the outputs (Fries and Taci, 2004). Thus, the total cost of this study is the sum of the total operating cost and interest expenses as the cost of the fund. These variables are widely accepted as the measures of banks' total cost and outputs (Kashian, Lin and Xue 2018; Fries and Taci, 2004).

Input prices – Sealey and Lindley (1977) mentioned that a significant part of banks' input prices is the cost of attracting depositors and providing services, and they include labour and capital and material costs used in producing services. The intermediation theory of banking also explains the same, which says banks use labour and capital to attract depositors (Monti, 1972; Sealey and Lindley, 1977). Sealey and Lindley (1977) stated that banks' production is a multi-stage process involving outputs processed by firms using labour, capital, and materials; the inputs are used to produce earning assets. It is also evident from Sealey and Lindley (1977) that the disagreement on banks' input prices is from the beginning of this production function. In the literature, slightly different variables are used as input prices, but most studies used the cost of labour and the cost of capital as banks' input prices. Therefore, following the literature, these two variables have been used here as the measure of input prices; they are – i) the 'staff expenses' as the cost of labour (overhead) and ii) other operating expenses as the cost of capital (Kashian, Lin and Xue, 2018; and Fries and Taci, 2004). The other operating costs are the cost of physical property and materials banks use for their daily operation.

3.2.3 Measure of growth

The growth measure of banks and NBFIs is not significantly different across the studies. Quarter or annual growth rate in lending has been taken as the measure of growth in almost all the studies in the literature (Noss and Toffano, 2016; Pintaric, 2016; Adesina, 2019; Roulet, 2018). However, there is a slight difference in data; most studies used banks' net or gross loan data, and few studies like Noss and Toffano (2016) applied M4 lending data to measure lending growth. The bank of England (2022) has defined M4 lending as a more economically relevant credit measure as it excludes lending to other financial corporations. Hence, as a precise measure of bank lending growth, this study has used the annual changing rate in 'net loan and advances to customers', excluding all lending to banks and other financial institutions.

Furthermore, to examine the differential effect of tighter bank regulation on NBFIs, this study has focused on the market and lending share of banks and NBFIs. Here the measure of growth is the changing rate in market share, which is the changes in individual institutions' share in total assets, and the changing rate in the individual lending share of the sample. The measure and approach taken by Buchak et al. (2018) and Irani et al. (2018) to examine the effect of tighter capital requirements on the growth of shadow banks are the closest to this measure and approach. The growth equations are as follows –

$$\Delta \text{ NBFIs loan share } (\%) = \left\{ \left(\frac{NBFIs\ loans_t}{All\ loans_t} - \frac{NBFIs\ loans_{t-1}}{All\ loans_{t-1}} \right) / \frac{NBFIs\ loans_{t-1}}{All\ loans_{t-1}} X100 \right) \right\}$$

$$\Delta\ NBFIs\ market\ share\ (\%) = \left\{ \left(\frac{NBFIs\ Assets_t}{All\ assets_t} - \frac{NBFIs\ Assets_{t-1}}{All\ Assets_{t-1}} \right) / \frac{NBFIs\ Assets_{t-1}}{All\ Assets_{t-1}} X100 \right\}$$

Furthermore, the studies mentioned above applied the nominal value; it can be because the magnitude of the data would be the same if they applied the real value. Therefore, following the literature, this study has also applied the nominal value and used inflation as a control. However, for the estimation's robustness check, this study has also applied the real value in the growth equation by adjusting the Consumer Price Index (CPI). It has also tested the financial institutions' categorical lending separately, including corporate, mortgage, consumer, and net loans, between 2015 and 2019 for the robustness and endogeneity check.

3.3 Control variables

This study has examined three different objectives, followed different methods, and developed different models to reach its objectives. The other factors or the controls that affect the key measures or 'explained variables' are seen different across the studies. As a result, this study has applied a set of commonly used control variables for each objective to address the other factors that also affect the 'explained variables' applied here, along with the key variables of Basel III. A set of factors seen in the literature provide incentives or deterrents to cost efficiency, bank returns, and the growth of banks and NBFIs. The studies in the literature have shown the bank return, cost efficiency, and growth as a function of bank-specific, industry and macro-economic specific factors (Pasiouras and Kosmidou, 2007; Athanasoglou et al., 2008; Staikouras and Wood, 2004; Goddard et al., 2004; Demirguc-Kunt and Huizinga, 1999; Abreu and Mendez, 2002; Fries and Taci, 2004; Altunbas et al., 2007; Mamonov and Vernikov, 2017; Lin, Doan and Doong, 2015; Nikiel and Opiela, 2002; Kraft and Tirtiroglu, 1998; Hasan and Marton, 2003; Grigorian and Manole, 2002). In this study, banks' regulatory level control variable has not been applied, as all the banks in the sample are under the same regulatory body. However, it has taken the ownership structure, bank size, bank operation, credit risk and macro-economic level factors into consideration and applied them as control variables following the literature. In terms of bank-specific factors, these studies emphasised bank capital, bank size, credit risk and bank operation-related indicators. Additionally, different interest rates, ownership structure, inflation and economic growth are the commonly applied indicators of macro-economic factors.

3.3.1 Bank size

Bank size plays a key role in market competition. Large banks are systematically more important, and they are more likely to be protected (Boyd and Gertler, 1994); there is an established 'too big to fail' theory that supports the impact of bank size on banks' performance. Based on the panel data of U.S commercial banks, Kim and Joh (2015) found that all the failed banks were small during the last financial crisis. Small banks also lose their charter value significantly during a stressed period, as they have less risk-shifting options. Thus, the small banks are the possible sufferers of a turbulent time. Banks' risk-taking behaviour is affected by the level of competition and market concentration within the industry, which impacts bank return and stability in a market (Carletti, 2008; Zigraiova and Havranek, 2016). Keeley (1990) found that the level of competition is negatively related to banks' performance which means the higher the market competition level, the more fragile the banks are. Nicoló and Loukoianova (2007), on the other hand, argued that higher market competition makes the banking sector more stable. They further showed that banks take higher risk in a less competitive market. Furthermore, Carletti and Leonello (2014) found that market concentration is positively related to banks' liquidity risk; greater market power leads the banks to take on more risk. They also interpreted that it is because it increases banks' opportunity cost of holding liquid assets. Beltratti and Stulz (2011) found that large and less risky banks performed better during the last financial crisis.

On the other hand, banks' cost efficiency can vary depending on their market power; for instance – large banks can offer their loan at a lower price than smaller banks, as the large banks mostly have the advantage of a lower cost of funds. According to the deposit insurance theory, a higher market share gives banks incentives to take on more risk (Boyd and Runkle, 1992). On the other hand, from the risk-taking perspective, production technologies are unimportant, and size plays no role in the theory. If all insured banks operate under the same regulatory framework, this theory predicts no relationship between bank size and efficiency. Moreover, the intermediation theory predicts that cost efficiency is related to bank size (Boyd and Prescott, 1986). It supports the "too big to fail" theory, and it has explained that it is because of their cost efficiency. Large banks have the advantage of contracting a large number of customers, which is assumed to bring diversification in asset quality. Diversification reduces the cost of overcoming information asymmetry. This theory has also been supported by Sapci and Miles (2019); they hypothesised that larger banks grow most likely because they receive higher returns and attain cost efficiency by large-scale outputs. In central European countries, bank size was found negatively related to banks' costs (Košak et al., 2009). However, Boyd and Stanley (1998) found that the smaller banks are the most cost-efficient in the US and their efficiency significantly decreases when they grow.

3.3.2 Ownership structure

Banks' ownership and capital structure have been found to impact banks' risk-taking behaviour. Diverse ownership of banks incentivises bank risk with fund collection from depositors and bondholders (Galai and Masulis, 1976). Here, the depositors can imperfectly monitor and control the actions of the owners, who tend to increase the value of their share by increasing the underlying asset risk of banks. The actions to increase the value of equity shares and asset risk also depend on the interest of the bank managers. The privatised banks have greater control over the management and tend not to take more risks (Jensen and Meckling, 1976; Demsetz and Lehn, 1985). However, when the shareholders have a special power and have diversified capital, they may influence the managers to take a greater risk through the board of governance (Beltratti and Stulz, 2011). Furthermore, Klomp and De Haan (2015) claimed that higher capital requirement gives more incentives to the shareholders, as it increases banks' profitability. The capital requirement is also a risk-sharing channel where shareholders get incentives.

Moreover, Banks' strategies vary because of the nature of customers' preferences, product type, quality of information, production methods, etcetera, which are driven by the differences in their ownership structure. Most countries have three types of ownership structures: state-owned, private commercial, and foreign banks. In some countries, state-owned banks are found to be more efficient than their private and foreign-owned counterparts (Hart, Shleifer, and Vishny, 1997), but in many other countries, the state-owned banks are seen as comparatively less efficient, and even in some countries, the state-owned banks are found extremely inefficient (Dewenter and Malatesta, 2001). Following the Stochastic Frontier Analysis approach, Mamonov and Vernikov (2017) found that the technical efficiency scores of domestic private and foreign banks are 84.4 and 62.9 per cent, respectively, and the state-owned banks scored 82.6 per cent. However, in the EU, state-own banks are the least efficient in terms of cost efficiency. The same result has been found in south-eastern European countries.

3.3.3 Bank operation and credit risk

The profit-maximising banks maximise the spread between deposit and loan rates (Djalilov and Piesse, 2016). Banks generally rely on the money market when they have a liquidity shortage. Klomp and Haan (2015) stated that if banks' dependency on the money market increases significantly to maintain their liquidity by purchasing or borrowing funds, they will be more likely to suffer from illiquidity risk in future. It has been explained that a lower level of liquidity and poor asset quality as two major factors for bank failure, and these are directly related to bank operation and indicate banks' credit risk.

Bank operation and risk-taking behaviour have been found to affect bank cost. Non-Performing Loans (NPL) and 'Loan loss Provision' (LLP) have been treated as a measure of banks' credit risk and operational efficiency in the literature (Berger and De Young, 1997). If the operational team is incompetent, they would not be able to appraise the value of the collaterals appropriately for loans.

It might result in being unable to control banks' operating costs, leading to a significant increase in NPL and LLP. The changes in the NPL also indicate the expected future loan loss. Furthermore, Rossi, Schwaiger and Winkler (2009) explained the agent-principal theory for banks' risk-taking behaviour. They hypothesised that 'managers are not risk-neutral; their behaviour can increase or decrease the level of bank risk. They further mentioned the fundamental theory of finance, which suggests that diversification in the loan portfolio reduces bank risk, and they measured the risk by LLP. Two fundamental hypotheses are found in the literature about bank risk and cost efficiency. The first one is called the 'monitoring hypothesis', suggesting that loan diversification for minimising costs might make the banks less cost-efficient. The second hypothesis explains that managers may also be risk-averse, and to provide low-risk loans, they may incur additional costs for the loan granting process and monitor the performance of those loans to reduce the risk.

3.3.4 Interest rate and macro-economic factors

Levine et al. (1999) stated that, generally, high-income economies have low inflation, and low-income economies are subject to high marginal inflation. Gross and Semmler (2019) further explained the role of monetary policy in an economy's stability and controlling inflation. The credit flow of an economy has been explained as one of the root causes of financial instability and inflation. Typically, the monetary policy concentrates on inflation and real outputs by devising the interest rate. However, many economists argue that the economic cost may outweigh the benefits of outputs and employment by concentrating on inflation and real outputs. Furthermore, by controlling the credit flow and credit cost, the monetary policy affects both the supply and demand side of credit flows, where banks play the role of key suppliers (Gross and Semmler, 2019). In the literature, different types of monetary policies have been seen, which have been developed targeting credit flow, inflation and outputs like the models developed by Svensson (1997); Schularick and Taylor (2012) and Gross and Semmler (2017). Inflation can affect banks' performance both ways, negatively and positively. If the banks can predict inflation and credit demand for the near future, they could adjust the interest rate accordingly. It might minimise their net interest cost. However, if the banks fail to predict these, they might have significantly higher interest costs (Athanasoglou et al., 2008). Flamini et al. (2009) stated that inflation, GDP, and industrial concentration are the most common external determinants of bank return. The GDP of an economy has been mentioned as a closely related external factor for bank performance. When the GDP increase, the loan demand in banks also increases cyclically. It has also been stated that slower GDP growth leads to poor credit quality, negatively affecting banks' profitability.

Furthermore, Giulioni (2014) explained two popular concepts of term-structure interest rates and banks' behaviour. The first one is known as the 'pure expectations' theory, which suggests that the long-term interest rate is equal to the serial sequence of short-term interest rates. If banks' liquidity position is explained by the 'pure expectations' theory where maturity is not relevant to cost or return, the regulatory liquidity requirements will seldomly explain banks' profitability. The second one is known as 'liquidity preference', where the long-term interest rate is explained as equal to a 'serial sequence of short-term interest rates' and a premium on the top, which has been explained as an increment for long-dated security which has an impact on bank return. Any changes in the interest rates affect banks' liquidity risk and, ultimately, bank return. Giulioni (2014) stated that because of short-term liquidity requirements, banks would suffer from the opportunity cost of investing more funds in short-term securities rather than long-term investments. On the contrary, the banks might also suffer from the higher cost of funds, as the long-term funds and capitals are more expensive than the short-term. Banks are expected to increase both the long-term and short-term liquidity during a normal economic period, but regulatory control is imposed during a crisis or in an unusual period.

4. Methodologies and models

This study has applied the IV GMM to investigate the correlation between liquidity risk and bank capital and their effect on bank return and cost efficiency. The cost efficiency of banks has been estimated using SFA panel data models. Lastly, the growth of the banks and NBFIs have been examined using the pooled OLS and random effect models with the difference-in-difference treatment effect. All the approaches followed, and the models developed have been detailed in this chapter.

4.1 Methodologies

4.1.1 Methodology for pre-step and to examine the impact on bank return and cost efficiency

This study has applied the IV GMM to examine the correlation between liquidity risk and bank capital and their effect on bank return and cost efficiency.

The Instrumental Variables or IVs approach is a statistical tool applied to experimental data that fails to satisfy all assumptions needed for an unbiased implication (Pokropek, 2016). The IVs are called instruments and are applied to determine an exogenous part of the variability from the endogenous predictor. In an IV estimation, the instrumental variable *Z* is an additional variable that estimates the causal effect of *X* on *Y.* The additional or instrumental variable *Z* is generally uncorrelated of all variables and effect *Y* through its effect on *X* (Pearl 2000). Therefore, the instrumental variable *Z* is not related to *Y,* but it is related to *X* and *Z* is not causally affected by *X, Y* or the error term μ. In this approach, one or multiple instrumental variables can be used in an equation (Pokropek, 2016).

GMM is a generic method for estimating parameters in statistical models and well known in econometrics for more than 100 years. The first assumption of GMM estimation is that there are a set of L moment conditions that the K -dimensional parameters of the interest, β should satisfy. The assumption is made by applying the population moment condition - $E(Y_t, \beta) - \mu = 0$ (Wooldridge 2002). Under suitable regulatory conditions, the GMM estimator is consistent and $\sqrt{\mathrm{T}}$ asymptotically normally distributed $\sqrt{\mathrm{T}}(\beta - \beta_o) \rightarrow N(0, V)$. It is also well known as a dynamic panel data estimator. It controls the endogeneity of the dependent variable in a dynamic panel data model when there is a correlation between the explanatory variables and the error term. It also controls omitted variables bias, unobserved panel heterogeneity and measurement error. In a linear regression model with an endogenous regressor, γ and μ are $\mathrm{N} \times 1$ vector, β is a $K \times 1$ vector of unknown parameters, and X is a $\mathrm{N} \times \mathrm{K}$ matrix of explanatory variables. GMM is specially designed for panel data where there is small T and large N panels independent variables which are not strictly exogenous; and where there is arbitrarily distributed fixed effects which is about having heteroscedasticity and autocorrelation within panel and groups.

It is explained above that IVs are instrumental Z variables, and IV GMM is an instrumental variables estimator implemented using the GMM. Baum (2014) mentioned that conventional IV estimators like 2SLS, which is the extension of OLS, are special cases of IV GMM. Gourieroux et al. (1994) illustrated that the IV GMM is asymptotically more efficient than the OLS estimation. They also stated that the efficiency gain is linked with conditional heteroscedasticity.

The IV GMM model is –

$$y = X\beta + u, u \sim (0, \Omega)$$

With $X(N \times K)$ and define a matrix $Z(N \times \ell)$ where $\ell \geq K$; this is what IV GMM estimator is. The ℓ instruments give rise to a set of ℓ moments:

$$g_i(\beta) = Z_i u_i = Z_i(y_i - X_i\beta), i = 1, N$$

Where each g_i is an ℓ vector, and the method of moment approach consider each ℓ moment equation as a sample moment, which can be estimated by averaging over N:

$$\bar{g}(\beta) = \frac{1}{N}\sum_{i=1}^{N} Z_i \left(y_i - X_i\beta\right) = \frac{1}{N}Z'u)$$

The GMM estimator selects an estimate that solves $\bar{g}(\beta\hat{}_{GMM}) = 0$ (Baum 2014).

If $\ell = K$, the estimation would exactly be identified by the order condition meaning the number of additional instruments are same as the right-hand endogenous variables. It causes a problem in method of moment estimation that is the K equations in Kunknowns, and Baum (2014) mentioned that there is a unique solution for this, which is equivalent to the standard IV estimator –

$$\beta\hat{}_{IV} = (Z'X)^{-1}Z'Y$$

Furthermore, in terms of overidentification ($\ell > K$), a set of K instruments can be defined:

$$X\hat{} = Z(Z'Z)^{-1}Z'X = P_Z X$$

It gives rise to 2SLS estimator:

$$\beta\hat{}_{2SLS} = (X\hat{}'X^{-1}X\hat{}'y = (X'P_Z X')^{-1}X'P_Z y$$

Baum (2014) explained that in 2SLS with overidentification ($\ell > K$), the ℓ instruments are boiled down to the K needed by defining the P_Z matrix. However, this reduction is not necessary in IV GMM; a weight matrix is generally employed to choose $\beta\hat{}_{GMM}$ which makes $\bar{g}(\beta\hat{}_{GMM})$ close to zero. When there is $\ell > K$, all ℓ conditions cannot be satisfied; hence a criteria function is used to improve the estimator's efficiency. Here the GMM minimizes the criterion by –

$$J(\beta\hat{}_{GMM}) = N\bar{g}(\beta\hat{}_{GMM})'W\bar{g}(\beta\hat{}_{GMM})$$

Where W is a $\ell \times \ell$ symmetric weighting matrix. Baum (2014) explained that IV GMM is purely the standard IV estimator when the errors satisfy all classical assumptions $S = \sigma_u^2 I_N$ and the weighting matrix is proportional to the identity matrix.

It has been mentioned above that the GMM is a well-known dynamic panel data estimator. Arellano and Bond (1991) first proposed this dynamic panel data approach, originally entitled difference GMM, and its extended estimator is System GMM (Baum, 2013). One of the key aspects of Arellano and Bond (1991) that echoes the IV GMM is the assumption that the necessary instruments are 'internal'. The estimators allow to include external instruments. The X_{it} in these estimators includes exogenous regressors, W_{it} are predetermined and endogenous regressors. Baum (2013) explained a potential weakness of Arellano and Bond (1991): when the variables are close to random walk, the lagged levels are rather poor instruments for the first difference variables. Furthermore, the 1st difference magnifies the gap of unbalanced panel data, so a weaker result could be found with unbalanced panel data.

Baum (2013) explained that in GMM panel data estimation, instruments could be GMM-style or IV-style. The GMM-style instruments follow Arellano–Bond strategy, which uses multiple lags. The IV-style instruments follow the instrument matrix. The choice of Weight Matrix (W_T) affects the asymptotic variance of the GMM estimator, and an optimal GMM estimator of β may be obtained by choosing W_T (Hansen, 1992). The common weighting matrix seen in the literature is - Two-stage Least square (2SLSs): $W_T = \hat{\sigma}^2 Z'Z/T)$ where $\hat{\sigma}^2$ is an estimator of the residual variance based on an initial estimate of β; 'White weighting matrix' for heteroskedasticity consistent estimator of the long-run covariance of $Z_t u_t(\beta)$ based on an initial estimate of β; Hac-Newey-West weighting matrix for heteroskedasticity and autocorrelation consistent estimator. Furthermore, the diagnostic tests for overidentifying restriction and endogeneity validate the model. If there is heteroskedasticity, those tests will show the models as invalid. The IV regress can also address this issue using the "robust" standard errors.

It is well recognised that IV GMM can generate efficient and consistent results in the presence of heteroskedasticity (Levine et al., 2000; Baum et al., 2002). On the other hand, the conventional IV estimator (OLS) with the robust standard error is comparatively inefficient (Baum et al., 2002). Levine et al. (2000) applied both IV GMM and OLS with macro-economic and bank level data where they used the OLS estimation for consistency check. This study has also followed almost the same approach where it applied the IV GMM in the main body and OLS for a robustness check (appendix). It applied the IV GMM with and without lagged dependent variables and put the estimation with lagged dependent variables in the appendix.

This study has applied the linear moment conditions, which require the instrumental variables Z to be uncorrelated with the error term. It is explained above that the instrumental variable Z can only affect the dependent variable through the explanatory variables and cannot have an independent effect on the explained variable. In the context of this study, it has been assumed that different interest rates on deposits affect banks' liquidity risk through the cost of funds, and interest rates on different macroeconomic variables, also known as regulatory mechanisms, affect the bank return and cost efficiency through liquidity risk. Levine et al. (2000) demonstrated that an efficient result could be derived using the IV GMM and conventional OLS cross-section method. Furthermore, they emphasised the overidentifying restriction test for the validity of the moment conditions and the consistency of the estimations.

4.1.2 Methodology to estimate banks and NBFIs' growth and differential impact on NBFIs

This study has developed three different panel data models to examine the growth of banks and NBFIs and the differential impact on NBFIs in terms of Basel III implementation.

The difference-in-difference treatment effect has been applied here to examine the differential impact of liquidity and bank capital on NBFIs. This approach is generally accepted as an equivalent estimation to a fixed effect model (Autor, 2003; Angrist and Pischke, 2009; Besley and Burgess, 2004). It is predominantly used to obtain causal estimates of a policy change or any other change affecting different subgroups at different points (Lechner et al., 2015). It evaluates the impact on outcome Y over a population of individuals or a subgroup. The group that receives treatment is given status (for example) T = 0,1, where 0 is the control group which do not receive treatment, and 1 indicates the treatment group or the individuals who receive treatment. Furthermore, in terms of the time effect, the period t = 0,1, where 0 is the pre-treatment period before the treatment group receives treatment, and 1 is the post-treatment period after the treatment group receives treatment (Kuminoff, 2020). However, a different operator can be used based on an author's preference. In this study, the treatment group are NBFIs (1), and the control group (0) are banks; the pre-treatment period (0) is from 2011 to 2015 and the post-treatment period (1) is from 2016 to 2019.

The difference-in-difference model is –

$$Y_{it} = a + \beta T_{it} + \gamma t_{it} + \delta(T_{it} \times t_{it}) + \varepsilon_{it}$$

Where a is the constant term, β is the treatment group (1) specific effect over the period t showing the average permanent difference between the treatment and control groups. The γ is the period common to the treatment (1) and control group (0). Then δ is the true effect of the treatment, which is $T \times t$, and in the context of this study, they are $NBFIs \times year$.

The studies in the literature mostly used OLS and fixed effect models, based on their data set, to investigate the differential impact on the growth of different financial institutions (Irani et al., 2018; Buchak et al., 2018; Martinez Miera and Repullo, 2019). Therefore, following the literature, this study has applied the OLS, and Random Effect (RE) models after the relevant diagnostic tests of the data set, showing which model suits the data sets best.

In general, there are three different methods for simple linear panel data models; they are - i) pooled OLS, ii) fixed effect, and ii) random-effect models. It needs to meet some preconditions to assess the appropriateness of fixed and random effect estimates in a data set. The Hausman test is formulated and widely accepted in the literature to choose between the fixed and random effect models. Here the null hypothesis explains that α_i are distributed independently of the X_i variables; if correct, the fixed effects estimate will be inefficient because it involves an unnecessary set of dummy variable coefficients. On the other hand, the random effects estimate will be subject to unobserved heterogeneity bias if the null hypothesis is rejected (Dougherty, 2007).

The null hypothesis has been accepted for all three models of the third objective, which means the random-effects model is appropriate for the data sets of all models. Furthermore, Dougherty (2007) mentioned that after selecting the random effects model, it needs to consider if there are any unobserved effects at all. He said that it is possible that the model is well specified and there is no individual-specific α_i term. He suggested applying pooled OLS in this situation. Applying pooled OLS gains efficiency by not attempting to allow for non-existent within-group autocorrelation, and it uses the advantage of finite-sample properties of OLS instead of relying on the asymptotic properties of random effects. There are many tests to detect the presence of random effects; the Breusch-Pagan Lagrange Multiplier (LM) test is the most commonly used test for this. The test statistics have a chi-squared distribution and one degree of freedom where the null hypothesis says no random effects. After conducting the Hausman test, this study has conducted the Breusch-Pagan Lagrange Multiplier (LM) of all models. It has been found that the common constant method or pooled OLS method is appropriate for the first and second models of this objective, where the growth of banks and NBFIs has been estimated separately, and the random-effects model is found appropriate for this objective's third model, where the difference-indifference treatment applied. A pooled OLS method is as follows –

$$Y_{it} = a + \beta X_{it} + u_{it}$$

Where the variable *Y* and *X* have both *i* and *t* for *i* = 1,2,3……., N sections and *t* = 1,2,3….*T,* time period.

4.1.3 Approach for cost efficiency estimation

This study has applied five different SFA panel data models to examine the cost efficiency of banks in Bangladesh.

Like productivity measure, cost efficiency is also measured with the unit of outputs for a given level of inputs, also known as technical efficiency in econometric estimation. Thiry and Tulkens (1988) stated that along with statistical and non-statistical methods, the production frontier could also be estimated by the technical knowledge held by the engineers. However, the statistical and non-statistical methods with quantitative input and output have been widely accepted and developed by the economists like the approach written by Forsund, Lovell and Schmidt (1980) and further developed and applied by Forsund and Hjalmarsson (1987) to the industry structure. There are different estimation methods for the production frontier. Thiry and Tulkens (1988) mentioned four different methods for estimating the production frontier; they are –

i) Non-parametric frontier
ii) Non-statistical estimation of a deterministic parametric frontier
iii) Statistical estimation of a deterministic parametric frontier and
iv) Estimation of a stochastic parametric frontier

Estimation of non-parametric frontier: For determining the production frontier Deprins, Simar and Tulkens (1984) first proposed a nonparametric estimating method. This method was developed from the solo assumption of input and output disposability. Thiry and Tulkens (1988) said that Farrell's (1957) was the first to suggest a method to measure technical efficiency based on production frontier (see Farrell's 1957). The method was non-parametric because it did not require presenting the frontier with estimated parameters by a function. They further provided the measurement method to calculate technical efficiency. They assumed the production frontier as a staircase shape, where the position of each stair is determined by an observation that is deemed efficient. They set the frontier as a boundary and defined it as the 'free disposal hull of the data set'. They set the 'efficiency degree' at 1 or 100 in percentage. The efficiency was measured with the input and output ratios, but they are not based on statistical interference.

Non-statistical estimation of a deterministic parametric frontier: non-statistical estimation of a deterministic parametric frontier is defined as – $\boldsymbol{DEF} = \boldsymbol{Y^0}/\boldsymbol{Y}^*$

Where the DEF is technical efficiency degree, and the parametric function of the production frontier is - $Y^* = f(X, a)$ or $InY^* = In\,f(X, a)$ where a is the vector for the constant parameter and the function may vary with the different forms like Cobb-Douglas or translog function. There will be a difference between $Y^{*}\ and\ Y^{0}$ if there is technical inefficiency and u has been defined here as $u = InY^{*} - In\,Y^{0}$ and it is non-negative, but the shortcoming here is to estimate the parameters of function f (X, a). However, this estimation can be conducted by solving the mathematical problem (Aigner and Chu 1968). This method also has shortcomings with the quadratic form and residual square. This estimation's advantages are that its frontier is continuous and provides technical efficiency. It also estimates the usual features of production function like scale and substitutions elasticity. However, the shortcoming of this method is that the number of observations deems efficient depends on a priori on the number of parameters specifying the function. It makes the inefficiency cases greater than those identified by the non-parametric approach.

Statistical estimation of a deterministic parametric frontier: This approach assumes discrepancies between the estimated function and the production situation observed especially technical inefficiency. The estimation may be provided with statistical properties using Maximum Likelihood (ML), 'corrected' ordinary least squares or 'displaced' ordinary least squares methods.

The frontier function *f* may be estimated by applying the classical ML method to specify a distribution for a one-sided residual. This method has many distributions: truncated normal distribution, gamma, exponential, log-normal or log-logistic. Here, the exponential adjustment with the ML method matches the linear programming adjustment; and the adjustment of a truncated normal distribution with ML matches the quadratic programming adjustment (Schmidt, 1976). Thiry and Tulkens (1988) said that these exponential and truncated normal distribution laws are void of sufficient conditions to ensure the usual asymptotic properties of the ML estimators. If the estimators lack such qualities, one of the other four laws should be applied. They further stated that the major shortcoming is that the result varies with the distribution chosen for the residual u.

The estimation of the production frontier is obtained using Ordinary Least squire (OLS) as a first step, where the presence of inefficiency is ignored. This 'corrected' OLS or COLS method adjust the constant term in the second step by using the central moment of the OLS residual with the shift of the 'mean' function to $In\,f(X;a)$ frontier. However, there are two major shortcomings of this method. Firstly, the estimate of the residual, frontier and 'mean' production function, and ultimately the efficiency measure of the observations may vary depending on the distribution applied for the residual (u). Secondly, it does not guarantee that the mean function will shift sufficiently after correcting the constant term. Thus, any estimation derived using this method cannot be trusted wholly.

On the other hand, the 'displaced' Ordinary Least Squire (DOLS) is very similar to that of COLS. This method adjusts the constant of the 'mean' production function estimated by OLS (Thiry and Tulkens, 1988). Compared with COLS, this method adjusts the u_u with the highest positive OLS residual. Though, the estimation of the a_0 constant term of this method is consistent, but the efficiency measure is biased and unreliable.

Estimating stochastic parametric frontier: In terms of Stochastic frontier estimation, a random error v, is added to the relation. The Cobb-Douglas frontier model integrates the error term in efficiency u and random error V, making the measure symmetric. It takes the measurement error, non-observed factors, especially the random shocks, into account. This random error term of the Stochastic frontier approach is like the classical econometric 'noise'. This Stochastic Frontier analysis approach has been adopted for this study, which has been explained by Thiry and Tulkens (1988) as the straightest way of representing a production process using statistical data.

Two mostly used approaches - Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis (DEA) – are used in the literature to measure banks' cost efficiency. The DEA is a non-parametric approach for efficiency estimates. The key difference between the SFA and DEA approaches is the techniques of measuring inefficiency from random errors. The DEA approach imposes less structure on the efficiency frontier and does not address the random error results from other measurement errors and data problems. Here, it assumes that the panel data is consistent over time, so the inefficiency of banks will also be consistent, and the random errors tend to be average during the period. Furthermore, inefficiency estimation is the difference between the average residual of the estimated cost function and the institutions' cost frontier. These conditions would be a considerable shortcoming of applying DEA for measuring the banks' cost efficiency in Bangladesh in terms of Basel III implementation, as every year, there is a degree of uncertainty after adopting this new regulation.

On the other hand, the SFA is a parametric approach that addresses random errors. Here in SFA, the errors consist of inefficiency, which follows a symmetric distribution. The application of different SFA panel data models also helps to compare the results and to identify if there is any biasedness in the estimation of any specific model or models. SFA has widely been used in the literature, especially for cost and production efficiency (Filippini, Greene and Farsi, 2005; Greene, 2004, Greene, 2002a.b.; Sakata, 2004; Fries and Taci, 2004). It was originally developed by Aigner, Lovell, and Schmidt (1977), and the formulation which serves as the foundation for other variations is –

$$Y = \beta'\mathrm{X} + v - u,$$

Where *y* is the outcome or goal attainment and $\beta'\mathrm{X} + v$ is the frontier goal; $\beta'\mathrm{X}$ is the deterministic part of the frontier, and *v* $[0,\sigma_u^2]$ is the stochastic part. These two-part together constitute the 'Stochastic Frontier', and the μ is the inefficiency. This is the normal-half normal distribution model, which forms the basic form of the stochastic frontier model. μ is the amount by which the observed individual fails to reach the optimum, which is - $\mu = |U|$ and $U \sim N[0, \sigma_u^2]$ and the formation changes to $v + u$ for the cost frontier in which the optimum is a minimum, and u is the inefficiency.

The SFA estimation has both time-varying and time-invariant panel data models. Filippini et al. (2005) have shown that an unbiased estimation can be obtained through a comparative result of time-varying and time-invariant models. Therefore, following Filippini et al. (2005), this study has applied three time-invariant and two time-variant SFA panel data models to disentangle time-invariant heterogeneity from time-variant inefficiency. It has explored the advantage of the Fixed Effects (FE) model to have an unbiased and compared estimation of the cost function. The alternative models have been applied to compare the coefficients of the cost function and inefficiency measures. The estimations of the conventional FE model are assumed to be unbiased with relevant tests; hence it has been used as benchmark estimation. The conventional fixed or random effects panel data model controls the unobserved heterogeneity, but this unobserved time-invariant heterogeneity is considered as inefficiency in SFA models (Filippini et al., 2005). The approach proposed by Greene (2004) distinguishes heterogeneity, like external effects, from cost efficiency by integrating an additional stochastic term representing inefficiency in both fixed and random effect models. Here, the True Random Effect (TRE) models, a random-effects model with normal-half normal distribution, has combined a conventional random-effects model with a skewed stochastic term representing inefficiency. A separate stochastic term for latent heterogeneity is included in this extended model. This study has applied the Cobb Douglas (log-linear) functional form for the cost efficiency estimation following Filippini et al. (2005).

The formation of the cost frontier for the panel data set of this study is as follows –

$$Y_{it} = \mathrm{X}_{it}\,\beta' + v_{it} + u_{it},$$

Where, Y_{it} is the total cost, and X_{it} is the matrix of input and output prices. $v_{it}$is the error and $u_{it} > 0$ is the technical inefficiency of banks *i* over the *t* period.

4.2 Empirical models

Different models have been developed for different questions and objectives. The empirical models developed for each question and objective are provided below.

Q0: How does the bank capital determine the liquidity risk?

Correlation between bank liquidity and bank capital with other correlates

Pre-step model

$$LR_{it} = \alpha + X_1 LR_{it-1} + X_2 CAR_{it} + X_3\ LNTA_{it} + X_4 NIM_{it} + X_5\ NPL_{it} + X_6 5\ Y\ T\_Bond_t + X_7 LNGDPC_{t-1} + X_8 INF_t + \ \mu_{it}$$

$$IE/TL_{it} = 1MDR_t + 3MDR_t$$

LR is banks' *i* liquidity risk at time *t*, which is of 4 different liquidity risk measures from the literature; they are – 'finance Gap' (*FGAP*), Net Loan to Total Customer and Short-term Funding ratio (*NETL/C&SF*); Liquid assets to Total Asset ratio (*LA/TA*) and Net Loan to Total Asset ratio (*NL/TA*) (Saunders and Cornett, 2006; Pasiouras and Kosmidou, 2007; Kosmidou, 2008; Naceur and Kandil, 2009; Bourke, 1989; Molyneux and Thornton, 1992; Barth et al., 2003; Demirgüç-Kunt et al., 2003). The first measure is the FGAP which is the difference between total customer deposits and banks' net loans divided by banks' total assets and turned into a percentage; here, the higher the ratios, the lower the vulnerability is to the funding liquidity risk. The second liquidity measure is *NETL/C&SF* of banks *i* over the period *t,* where the greater the ratio, the higher the probability of liquidity risk. The third measure of liquidity risk is the ratio of banks' *i LA/TA* over the *t* time, where the higher the ratio, the lower the funding liquidity risk is. The fourth liquidity risk measure is *NL/TA,* which is banks' *i* net loan to assets ratio over the period. CAR is the tier 1 capital to total asset ratio or leverage ratio, which is banks' *i* capital adequacy at time *t*, and *NPL* is banks' *i* non-performing loan ratio indicating credit risk over the *t* period. Furthermore, LNTA is the total asset of banks *i* in natural logarithms over the years *t* which refers to bank size; *NIM* is 'Net Interest Margin' ratio of banks *i* at time *t*; *LLP/TL* is Loan Loss Provision to Total Loan of banks *i* over the *t* period; these measures have been applied to control the operational and credit risk factors of banks *i*. *INF* is the Inflation, and *LNGDPC* is the changes in nominal GDP every year *t* over the selected period. Furthermore, the $Y\ T\_Bond$ is the interest rate on a five-year government bond over the *t* period.

IE/TL is the ratio of 'Interest Expense to Total Loan', banks' *i* cost of the fund over the period *t* and instrumented as endogenous to banks liquidity risk with the instruments – 1 month and 3 months average Deposit Rate over the year *t*. The instrumental variables Z have been used, assuming that the interest rates on different term deposits affect the liquidity risk through the cost of funds or banks' total interest expense.

4.2.1 Model for examining the effect of liquidity risk and bank capital on bank return

Model – 1

$$\Pi_{itk} = \alpha + X_1\Pi_{itk-1} + X_2CAR_{it} + X_3\mathrm{LNT}A_{it} + X_4NIM_{it} + X_5NPL_{it} + X_6LLP/TL_{it} + X_7LA/TA_{it} + X_8NL/TA_{it} + X_9 5YT\_bond + X_{10}GDP_t + X_{11}INF_t + \mu$$

$$FGAP = \mathrm{NETL/C\&SF}_{it} + R_t + 1MDR_t + 3MDR_t + 6MDR_t + 1\,YDR_t$$

$\mathbf{\Pi_{itk}}$ is bank *i* return at time *t* and measured at parameter k (k = Return on Asset (ROA) and Return on Equity (ROE). The instrument *FGAP*, which is the measure of liquidity risk, has been instrumented as endogenous to bank return with the instruments – $NETL/CandSF$, another measure of bank liquidity, interest rate spread, 1-month, 3-month, 6-month and 1-year average Deposit Rate over the *t* years.

CAR is the tier 1 capital to total asset ratio or the leverage ratio, which is banks' *i* capital adequacy at time *t*. *LNTA* is banks' *i* total assets in natural logarithm over the period *t,* controlling the bank size. *NIM* is Net Interest Margin ratio of banks *i* at time *t*, and *NPL* and *LLP/TL* are banks' *i* non-performing loan ratio and Loan Loss Provision to Total Loan ratio over the *t* period, indicating banks' operation and credit risk, respectively. *LA/TA* and *NL/TL* are banks' *i* exogenous liquidity risk measures over the *t* period. *5YT_bond*, *GDP,* and *INF* are the country's five-year government bonds, nominal GDP, and inflation, respectively, used to control the macroeconomic factors.

4.2.2 Models for examining cost efficiency and the effect of liquidity risk and bank capital on cost efficiency

This study has followed a two-step approach to examine cost efficiency. The cost efficiency has been estimated following the SFA panel data models approach, and the effect of liquidity risk and bank capital on cost efficiency has been examined in the second step by applying the IV GMM.

4.2.2.1 Model for cost efficiency estimation

Model – 2.1

Q2a: How far cost-efficient are banks?

The log-linear model specification for the cost efficiency is –

$$lnTC_{it} = a_0 + \sum_{j=1}^{2} \beta_j \ln w_{jit} + \sum_{m=1}^{2} \gamma_m \ln \gamma_{mit} + v_{it} + u_{it}$$

Where $ln\mathrm{TC}$ is banks' *i'* Total Cost' over *t* time which is the sum of banks' operating and interest costs in a natural logarithm. The variables applied here are banks' two outputs w_{jit} where *j*= 1,2, which are the ratios of 'Net loans to Total Assets' and 'securities to Assets' of banks *i*, turned into percentage and Υ_{mit} is two input prices (m=1,2) – cost of labour (staff cost) and cost of capital (other operating costs), which have turned into a percentage with total assets. The Stochastic model developed in this study is based on Greene's (2004) Stochastic frontier formulation, which fits various models for analysing the Cobb-Douglas cost function. All these models are the extension of the original models proposed by Aigner et al. (1977).

This study followed the cost efficiency estimation technique of Filippini et al. (2005), where they applied both time-variant and time-invariant SFA panel data models to reduce time-variant heterogeneity bias and to derive an unbiased estimation. This study has also applied five different SFA panel data models following Filippini et al. (2005) to derive unbiased efficiency scores and parameters. Model 1 is a Fixed Effect (FE) model, where the bank-specific effects have been considered as a constant parameter. The estimation is conducted through 'within-bank' variations; thus, the heterogeneity bias does not affect the result. Model 2 is the Random Effects (RE) model with the half-normal distribution and maximum likelihood method proposed by Pitt and Lee (1981), and Model 3 is Battese and Coelli's (1988) (BC88) maximum likelihood method with the truncated normal distribution. In these random-effects models, the inefficiency is estimated using a conditional mean by the inefficiency term proposed by Jondrow et al. (1982). It is assumed in these models that the bank-specific stochastic term a_i which represents banks' inefficiency is not correlated to exogenous variables, which is the limitation of these models. However, Filippini et al. (2005) explained that assuming cost-inefficiency uncorrelated to exogenous variables is reasonable, as these fixed and random effects models might overstate banks' inefficiency by including unobserved environmental factors. Model 4 is the 'True Random Effect' (TRE) model proposed by Greene (2002 a,b); here in this model u_{it} is the stochastic term with a normal-half-normal distribution, and the estimation method is based on the simulated maximum likelihood. It is assumed in this model that banks' unobserved cost difference, which remains constant over time, is driven by banks' unobserved factors rather than inefficiency. The inefficiency term in this model is assumed to be a random variable with the normal-half-normal distribution; that is, each period brings new idiosyncratic elements; in other words, the inefficiency is not persistent. Filippini et al. (2005) stated that this could be a reasonable assumption for the industries which constantly confront changes or new technologies. Therefore, the inefficiency of banks has been computed fundamentally in two different ways; the first assumption is that the persistence cost difference is related to unobserved heterogeneity, and in the second one, the source of inefficiency is the changes in idiosyncratic elements. Model 5 included Mundlak's (1978) specification, but it is the extension of model 4; it comprises the unobserved heterogeneity with explanatory variables. Mundlak's adjustment is an auxiliary regression which is –

$$a_i = y\bar{X}_i + \delta_i \qquad \bar{X}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} X_{it}\,, \delta_i \sim N(0, \sigma_\delta^2)$$

Where y is the corresponding vector of coefficient and X_{it} is the vector of all explanatory variables. In this model, the bank-specific stochastic term is divided into two components: the first component is explained by the exogenous variable, and the second one is orthogonal to the explanatory variables. When it minimises the heterogeneity bias, it allows for a time-variant inefficiency term which is the advantage of this model. It can avoid heterogeneity bias to an extent where an auxiliary equation can capture the correlation. In the stochastic part of this study, there are two aspects of the estimation. The first aspect is the estimation of the cost function coefficients, and the second aspect is the estimation of banks' inefficiency. The Hausman test has been conducted to confirm the firm-specific effects as the exogenous variables have not been applied in these stochastic models. Thus, the FE model is unbiased and can be considered a benchmark to compare the estimation of other models. Furthermore, the inefficiency estimation can be biased even if there is consistency in the coefficients across all models, as seen in Filippini et al. (2005), where they examine Swiss railway companies' cost efficiency. However, the heteroscedasticity and multicollinearity issues have also been considered, and related diagnostic tests have been conducted.

Here are the econometric specifications of different SFA panel data models applied for estimating cost efficiency.

	1	2	3	4	5
	FE	RE	RE	True RE	True RE with Mundlak Adjustment
Firm-specific component	Constant	Half-normal $N^+(0, \sigma_a^2)$	Truncated Normal	$N(0, \sigma_a^2)$	$a_i = \gamma X_i + \delta_i$ $X_i = \frac{1}{t_1}\sum_{t=1}^{T_i} X_{it}$ $\delta_i \sim N(0, \sigma_\delta^2)$

4.2.2.2 Model to examine the effect of liquidity risk and bank capital on cost efficiency

Model – 2.2

$$TE_{it} = \alpha + X_1TE_{it-1} + X_2CAR_{it} + X_3LLP/TL_{it} + X_4LLR/TL_{it} + X_5NPL_{it} + X_6LNTA_{it} + X_7MMR_t + X_8INF_t + X_9LNGDPC_{t-1} + \varepsilon_{it}$$

And instrumented indigenous variables are –

$$LA/TA_{it} = \mathrm{FGAP}_{it} + 3\ MDR_t$$

Where TE is the estimated technical cost efficiency of banks *i* at time *t,* which has been calculated following the SFA 'cost function' exp{−E(u|ε)} with five different models explained above.

LA/TA_{it} is banks' liquid assets to total assets instrumented by $FGAP_{it}$ and banks' 3DR (3 months deposit rate) as endogenous to banks' *i* technical efficiency (TE) over the t time. CAR is banks' *i* 'Leverage ratio', the ratio of Tier 1 capital to Total Assets over the period.

The explanatory variables *LLP/TL, LLR/TL* and *NPL* are banks *i* Loan Loss Provision, Loan Loss reserve and Non-performing Loan to Total loan ratios accordingly over the t period; these control variables have been taken as the measure of bank operation and credit risk. *LNTA* is the logarithmic form of banks' *i* total assets, demonstrating their size and market power at *t* time. In addition, three different macro-economic level control variables have also been applied in this model; they are MMR 'Money Market Rate'*, INF'* inflation' and *LNGDPC*, the changes in nominal GDP or nominal GDP growth ($USD) in natural logarithm over the *t* period in the country.

4.2.3 Models for investigating the effect of bank liquidity and capital ratio on the growth of banks and NBFIs and differential impact on NBFIs

Three different models have been developed to examine the growth of banks and the differential impact on NBFIs. Model 3.1 has been designed to examine the impact of capital ratio and liquidity risk on the growth of banks, and Model 3.2 focuses on the growth of NBFIs. Lastly, Model 3.3 examines the differential impact on the growth of NBFIs with the difference-in-difference treatment effect.

4.2.3.1 Model for examining the effect of liquidity risk and bank capital on the growth of banks

Model: 3.1

$$\Delta bank\_Lnand\_TA_{it} = a_{it} + X_1NIM_{\ it} + X_2LLP/TL_{it} + X_3LA/TA_{\ it} + X_4CAR_{it} + X_5INF_t + \varepsilon_{it}$$

$\Delta bank\_Lnand\_TA_{it}$ is the growth rate (%) in banks' *i* lending and total assets over the period *t,* which is the percentage changes from the previous year. LA/TA is the ratio of banks' *i* liquid assets to total assets over the period *t,* which is the measure of banks' liquidity risk. *CAR* is banks' *i* capital ratio over the period *t,* the ratio of banks' tier 1 capital to total assets. NIM is banks' *i* net interest margin applied as a control of banks' operation and performance over the period $t.$ LLP/TL is the loan loss provision ratio of banks *i* over the time *t,* which controls the operational and credit risk. Finally, INF is the inflation rate in the country over the period *t* applied to control the inflation.

4.2.3.2 Models for examining differential impact of bank liquidity and banks' regulatory capital on NBFIs

Basel III has been implemented in the banking sector in the country, and this study has examined if it has any differential effects on the growth of NBFIs. As mentioned above, Basel III was issued in 2010, and the countries following Basel regulations since 2012. As a result, a limited number of studies examined the differential impact on the growth of other financial institutions like NBFIs or shadow banking institutions. The studies seen in the literature have applied slightly different measures. Models 3.2 and 3.3 are the closest to the model developed by Buchak et al. (2018), where they examined the differential impact of fintech and tighter regulation on NBFIs' growth.

Model: 3.2

$$\Delta\Pi_{itk} = a_{it} + X_1 NIM_{\ it} + X_2 LLP/TL_{it} + X_3 LA/TA_{\ t} + X_4 RCAR_t + X_5 INF_t + \varepsilon_{it}$$

Where $\Delta\Pi$ is two key and two supportive growth measures *k* of NBFIs; the key measures are the percentage change in NBFIs' *i* loan and market share, and the supportive variables are the changing rate (%) in NBFIs' *i* loan and total assets from the previous year over the period *t.* The equation of the growth measures is the percentage changes in NBFIs' *i* market and lending share over the *t* period, which has been detailed above.

LA/TA is the average liquid assets ratio of all banks in the sample over the period *t,* and *RCAR* is the required capital assets ratio of banks in the country over *t* time. NIM is NBFIs' *i* net interest margin applied to control the NBFIs' operational performance over the *t* period. LLP/TL is NBFIs' *i* loan loss provision applied to control NBFIs' credit risk. Furthermore, INF is the inflation rate in the country over the *t* period. This Model has also applied the year fixed effect, demonstrating the difference in NBFIs' growth after implementing Basel III.

Model: 3.3

$$\Delta all\_Loanand\_Market\_Share_{\ it} = a_{it} + X_1 NIM_{\ it} + X_2 \frac{LLP}{TL}_{it} + X_3 \frac{LA}{TA_t} + X_4 RCAR_t + X_5 INF_t +$$

$$X_6 NBFIs_i \times year_t + \varepsilon_{it}$$

$\Delta\ all\ Loanand\_Market\_Share$ is the percentage change in all institutions' *i* loans (banks and NBFIs) and market share of the sample over the t period. The operation and credit risk of banks and NBFIs *i* have been controlled with *NIM* and *LLP/TL,* which are the 'net interest margin' and 'loan loss provision' ratios of both financial institutions *i* over *t* time, accordingly. *LA/TA* and *RCAR* are banks' average liquid assets ratio and required capital assets ratio, respectively, over the time t. *INF* is the yearly inflation rate in the country. Finally, the difference-in-difference treatment effect has been applied to examine the differential effect on NBFIs, where the $NBFIs_i$ have been applied as the treatment group.

5. Data

The data is from 2011 to 2019 and collected from four different sources. This period has been selected to avoid the pandemic effect and solely to focus on the Basel III implementation. The data on bank-specific variables have been collected from the Orbis Bank Focus database, and the data on macroeconomic-specific variables have been derived from the central bank website and International Monetary Fund (IMF) database. Furthermore, the NBFIs data has been derived from their annual reports.

In terms of bank-level data, the data of all scheduled banks was collected at the first stage. Then the foreign banks' data have been excluded because of their limited operation and unavailability of data for all variables applied. In addition, the data of newly incorporated banks whose data is available from 2014 and the data of small banks which operate within specific geographic areas for specific groups of people have also been excluded from the sample, as their size and area of operations are significantly small. However, the data of newly incorporated banks is homogeneous to the sample data. After excluding the data of these banks, a balanced panel data set of 31 mainstream banks have been applied for the empirical analysis. Most of the data on bank-specific variables are from the consolidated bank statement, and some data has been collected from the memo line and unconsolidated statements, which are not available in consolidated statements. The deposit rates instrumented in the GMM models are yearly average interest rates. The currency in the sample for bank-level data is in US$(000) transformed from the local currency of the country (TK) via World'Vest Base Inc by the database (Orbis) apart from the bank-level data of the third objective's model 3.3.

The data of NBFIs specific variables are in local currency, Bangladeshi TK, applied in Models 3.2 and 3.3 of the third objective. The bank and NBFI level data have been combined in model 3.3 in the third objective to examine the differential effect on NBFIs. Thus, all the bank-specific variable data for this model have been collected in local currency when combined with NBFI data to apply the treatment effect. Applying two different figures and currencies for the same equation could provide a biased or misleading estimation through the equation in percentage change. Thus, this issue has carefully been considered and used the same currency and figure to calculate the percentage change in lending and total assets when combined.

Figure 1: Bank and overall market growth of the sample

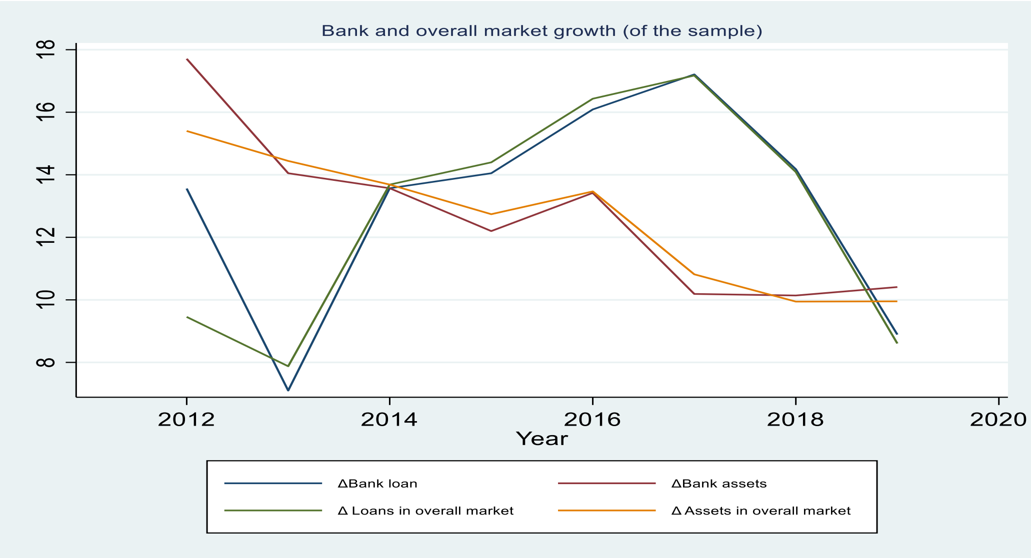

Figure 2: NBFIs' loan and market share of the sample and their growth rate

The growth rate in loans and loan share are the key measures for growth, and the growth rates in total assets and market share have been applied to support these key estimates in the third objective. The growth rates of bank loans and bank assets in Figure 1 show that they have little difference from the overall market throughout the period indicating that the banks largely influence the overall financial market. It also shows that the overall growth in bank loans was at its peak in 2017 and then decreased sharply following the next two years. However, the growth rate in overall bank assets fluctuated significantly less and was more stable after 2015 than the loan growth.

Figure 2 shows that the lending share of NBFIs increased from 4.40 in 2011 to 6.13 in 2017, and after that, this sector experienced marginally negative growth in lending share. It also shows a similar pattern in the market share of the sample. Figure 1 shows a significant change in the growth of the overall financial market after implementing Basel III, and the banks have the dominating influence. The NBFIs in the country have been growing slowly, and they hold nearly six per cent of the total lending share, significantly less than their banking counterparts, but they pose a contagious risk. The Financial Stability Board (2017) stated that they could enhance credit supply during a stable period and enlarge a systemic crisis when confidence falls. They further emphasised that the risk of NBFIs can easily spill over into the traditional banking system.

Banks' total cost and total assets, in Table 1, have been turned into a natural logarithm here. The mean, minimum, maximum and standard deviation of these variables indicates that the market is significantly competitive, as there is a small difference in the sample data. Moreover, the descriptive statistics show a significant difference in banks' liquidity risk levels. The high standard deviation of FGAP and LA/TA indicates that the banks follow different strategies for maintaining the level of liquidity risk. They apparently possess a different level of risk as there is a significant difference in the data. On the other hand, there is also a significant difference in banks' leverage ratio (CAR) compared to banks' cost and size. The Basel III minimum required leverage ratio is 3 per cent, and it is recommended to increase the minimum leverage ratio over the following three years, but the bank with the minimum leverage ratio in the sample is 3.308, which points out that some banks in the country find it challenging to comply with Basel III, but they have competitive market share and bank cost. The Bank of England has set the minimum required leverage ratio at 3.25, and it is 4 per cent in the USA. Moreover, it also shows that the inflation rate in the country was stable over the period in the South Asian context.

Table 1: Descriptive Statistics (Banks)

Variable	Obs	Mean	Std.Dev.	Min	Max
Bank Liquidity					
FGAP	259	.124	.088	-.116	.415
NETL/C&SF	261	82.545	9.415	52.400	109.470
LA/TA	249	13.546	5.997	2.120	37.540
NL/TA	261	67.486	6.927	44.830	83.540
Bank Return					
ROA	261	1.001	.48	-.410	3.660

ROE	261	12.000	4.762	-10.330	28.280
Cost Efficiency					
Total cost:					
ln TC	279	12.249	.467	11.197	13.649
Input prices:					
Cost of labour					
Staff Cost/Total Asset	279	1.208	.351	.533	2.663
Cost of capital:					
Other operating cost/Total Asset	279	.981	.511	.378	2.881
Outputs:					
Securities/Total Asset	279	15.278	7.614	3.178	40.656
Loan/Total Asset	279	66.375	9.29	29.663	83.673
Bank operation and credit risk					
LLP/TL	265	1.055	.892	-.110	9.734
LLR/TL	264	3.879	2.414	1.595	21.393
NPL	267	6.694	5.759	1.35	35.089
IE/TL	260	7.918	2.307	2.553	14.046
NIM	261	.697	.126	.296	1.130
Capital Asset Ratio/ Bank leverage:					
CAR	279	8.007	2.067	3.308	15.768
Bank size					
LNTA	261	14.746	.472	13.594	16.375
Macro-Economic Variables					
INF	261	6.564	.946	5.590	8.200
LNGDPC	261	9.227	.260	8.917	9.670

Interest rates					
1 MDR	261	.512	.510	.090	1.660
3 MDR	261	.747	.631	.170	1.910
6 MDR	261	.864	.590	.250	2.170
12 MDR	261	1.083	.471	.700	2.230
MMR	279	6.737	3.185	3.67	12.82
5 Y T_Bond	279	8.237	2.215	5.330	11.680

Table 2: Descriptive Statistics (Growth measures: Banks and NBFIs)

Variable	Obs	Mean	Std. Dev.	Min	Max
Banks					
Growth rate in Banks' loan and assets					
Δ Loan(%)	248	14.41	8.522	-7.978	47.388
ΔTA (%)	248	14.032	8.233	-5.508	46.35
Growth in NBFIs					
Δ Loan share (%)	150	4.038	22.763	-29.574	160.782
Δ Market share (%)	151	3.03	20.292	-32.553	142.583
Δ Loan (%)	149	16.542	20.781	-21.569	129.37
Δ TA (%)	151	16.203	23.314	-25.896	175.254
The overall growth of Banks and NBFIs					
Δ Loan share (%)	398	2.145	15.161	-29.574	160.782
Δ Market share (%)	399	1.81	13.319	-32.553	142.583
Banks and NBFIs' Operation					
NIM	448	3.078	2.182	-19.203	9.338
LLP/TL	444	1.071	2.632	-4.352	52.494
Regulatory Capital Requirement					

RCAR	450	10.694	.906	10	12.5
LA/TA (Bank average)	450	11.903	1.588	9.529	14.489

6. Empirical results

This study has developed different models to reach the objectives and answer the questions. The results of the empirical models developed are provided below.

All estimates of the IV GMM approach with and without lag-dependent (t-1) variables are identical; hence the results without lag-dependent variables are presented in the main body, and with lag-dependent variables are provided in the appendix. Furthermore, banks' cost efficiency and the determinants have also been estimated following a one-step approach, and the results are provided in the appendix.

How does the bank capital determine the liquidity risk? (pre-step)

Table 3 presents the determinants of banks' liquidity risk in Bangladesh, and the year-fixed effect results show the difference in the level of liquidity risk after Basel III implementation. The FGAP is the difference between 'Bank Loan and Customer Deposits', and 'LA/TA' is the ratio of 'Liquid Assets to Total Assets', where the higher the ratio, the lower the risk of funding liquidity. On the contrary, 'NETL/C&SF' and 'NL/TA' are 'Net Loan to Deposit and Short-term Funding' and 'Net loan to Assets' ratios accordingly, where a higher ratio indicates a higher risk of the funding liquidity. The results in Table 3 show that CAR, which is the capital ratio or banks' leverage ratio, is negatively related to FGAP and LA/TA and positively related to 'NETL/C&SF'. It shows that a 1 percentage point increase in capital ratio decreases the FGAP and LA/TA by approximately 1.39 and 1.31 per cent, respectively. Thus, the results reveal that well-capitalised banks retain less liquidity derived from customer deposits and invest less in liquid assets, generally short-term investments. On the other hand, banks' 'NETL/C&SF', which is the ratio of banks' illiquid assets and the opposite measure of FGAP and LA/TA, is positively related to banks' capital ratio. The results in Table 3 show that the elasticity between the NETL/C&SF and capital ratio is 1.55 percentage points. This positively related coefficient reveals that the higher the capital ratio, the more illiquid assets banks hold. Thus, the well-capitalised banks take a higher risk of funding liquidity than the less-capitalised banks in the country.

These findings are consistent with Distinguin, Roulet and Tarazi (2013), but they followed a simultaneous equation approach. In contrast, this study has applied all the liquidity measures separately and identified their correlation with bank capital. Following a simultaneous equation of liquidity risks may provide misleading results because a particular type of liquidity risk may not be correlated, but, being a simultaneous equation, it might be shown as correlated. For instance, NL/TA of this study is found not correlated to bank capital, but if all the measures had been equated simultaneously, taking their weighted value and made a single measure as Distinguin, Roulet and

Tarazi (2013) did, it might have shown NL/TA correlated as well. However, this study underpins the findings of Distinguin, Roulet and Tarazi (2013), although it has followed an individual measuring approach.

Furthermore, the NPL, banks' 'non-performing loan ratio', is also significantly related to banks' liquidity risk. They are positively correlated; banks' FGAP and LA/TA increase by 0.05 and 0.37 per cent, respectively, against a 1 per cent increase in NPL. The results also show that the 'NETL/C&SF'and 'NL/TA' are negatively related to NPL. It implies that banks with higher NPL provide less loans and advances to their customers and retain more liquid assets to manage the liquidity risk indicating their credit and operational management. However, the year fixed effect results of the liquidity risk estimates show no significant change in banks' level of funding liquidity risk after implementing Basel III in the country.

For the validity of an IV GMM estimation, it needs to pass two key diagnostic tests: the test of overidentifying restrictions and 'first stage regression'. The test of overidentification restriction shows if it is orthogonal to the error term, which tests the instrument's validity and whether they are over-identified. The second one is the 'first stage regression' test showing whether the model is valid. This study has also conducted the endogeneity test, which shows if the instrumented and instrumental variables applied are endogenous to the liquidity risks. All the IV GMM models applied here have passed all these diagnostic tests. The instrumented and instrumental variables applied for estimating the liquidity risk are found endogenous to FGAP and 'NETL/C&SF', but the measure of LA/TA and NL/TA shows that the instrumented variables can also be applied as exogenous variables for these regressions. Furthermore, the robust standard error cluster has been applied to all the regressions which control the heteroskedasticity across clusters of observations. All the diagnostic test results have been provided below the regression results and relevant tables.

Table 3: Determinants of liquidity risk

	(1)	(2)	(3)	(4)
VARIABLES	FGAP[1]	NETL/C&SF[2]	LA/TA[3]	NL/TA[4]
IE/TL	-0.0336*	3.2186	-0.5568	1.4214
	(0.0192)	(2.0568)	(1.1929)	(1.4806)
CAR	-0.0139***	1.5488***	-1.3472***	0.1885
	(0.0023)	(0.2601)	(0.1709)	(0.1874)
LNTA	-0.0160	4.0882	3.4930**	0.3053
	(0.0242)	(2.5461)	(1.6719)	(1.8306)
NIM	0.4346**	-33.5739*	-7.8774	-9.2110
	(0.1875)	(20.0200)	(11.8156)	(14.3330)
NPL	0.0050*	-0.7263*	0.3184**	-0.7562***
	(0.0028)	(0.3816)	(0.1568)	(0.2621)
5Y_Bond	0.0229**	-2.6781***	0.3664	-1.4057*
	(0.0097)	(1.0388)	(0.5868)	(0.7692)
LNGDPC	-0.1028*	8.3475	-10.9727**	7.9615
	(0.0588)	(6.6461)	(4.4830)	(4.9228)
INF	0.0130	-1.0269	0.0359	-0.6276
	(0.0096)	(1.1502)	(0.7300)	(0.8178)
2015-2019	-0.0304	2.6261	-2.3161	1.4845
	(0.0356)	(4.0510)	(2.6360)	(2.7669)
Constant	1.1032*	-38.3183	80.1855*	1.6174
	(0.5821)	(66.3440)	(43.6565)	(48.4588)

[1] Test of overidentifying restriction: H_o – instrument set is Valid and the model is correctly identified (Hansen's J, p = 0.1613), Test of endogeneity (orthogonality conditions) H_o – variables are exogenous (p = 0.0949), First-Stage Regression summary statistics: H_o – Instruments are weak (R-sq: 0.846, Ad R-sq: 0.832 and p = 0.000)
[2] Test of overidentifying restriction: H_o – instrument set is Valid and the model is correctly identified (Hansen's J, p = 0.5786), Test of endogeneity (orthogonality conditions) H_o – variables are exogenous (p = 0.0270), First-Stage Regression summary statistics: H_o – Instruments are weak (R-sq: 0.846, Ad R-sq: 0.832 and p = 0.000),
[3] Test of overidentifying restriction: H_o – instrument set is Valid and the model is correctly identified (Hansen's J, p = 0.3803), Test of endogeneity (orthogonality conditions) H_o – variables are exogenous (p = 0.2864), First-Stage Regression summary statistics: H_o – Instruments are weak (R-sq: 0.91, Ad R-sq: 0.904 and p = 0.000
[4] Test of overidentifying restriction: H_o – instrument set is Valid and the model is correctly identified (Hansen's J, p = 0.2390), Test of endogeneity (orthogonality conditions) H_o – variables are exogenous (p = 0.30) First-Stage Regression summary statistics: H_o – Instruments are weak (R-sq: 0.91, Ad R-sq: 0.904 and p = 0.000)

Observations	235	235	232	235
R-squared	0.3839	0.3207	0.2839	0.3465

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.1 Effect of liquidity risk and bank capital on bank return

Q1a: What is the effect of liquidity risk on bank return?

Q1b: What is the effect of capital ratio on bank return?

The results in table 4 show the effect of liquidity risk and bank capital or leverage ratio on bank return. Here, the ROA is the key measure and ROE is used as a supporting measure. It is because ROE may vary depending on the governing body's decision, but ROA presents banks' actual return against every unit of assets. The results show that the FGAP is endogenous to bank return and positively related; bank return increases by 1.43 per cent point for every 1 per cent increase in FGAP, indicating banks' cost of maintaining the funding liquidity risk. Furthermore, the leverage ratio (CAR) is positively related to bank return, which means the higher the capital ratio, the greater the bank return; so, the well-capitalized banks in the country make more profit. Thus, the well-capitalized banks operate with a higher level of liquidity risk (presented in table 3) by retaining less liquid assets and providing more loans to the customers indicating that the higher return partly comes from their higher risk-taking behaviour or an incentive to take a higher risk of funding liquidity. This result is consistent with Demirgüç-Kunt and Huizinga (1999); Barth et al. (2003); Pasiouras and Kosmidou (2007); Athanasoglou et al. (2008). However, the bank size and operation are negatively related to bank return. The results in table 4 show that bank return (ROA) decreases by 0.15 per cent against 1 per cent increase in bank size. Furthermore, the ROA decreases by 0.02 and 0.21 per cent for 1 percentage point increase in NPL and LLP/TL, respectively. In Addition, the macro-economic factors have been found not related to bank return. However, the year fixed effect results in table 4 show that the ROA from 2015 to 2019 was lower by nearly 0.12 per cent from other years, indicating the cost of implementing this new regulation or aftermath of implementing Basel III. After implementing Basel III, the interest rate on customer deposits increased, and the money market rate decreased (Appendix: figure 1), indicating banks' attempts to increase liquidity and regulatory action to keep banks' liquidity maintenance costs low to adopt this new regulation and stabilize the market. However, the results suggest that it decreased the bank return. The required bank liquidity changed, but the year fixed effect results in table 3 show that the level of liquidity risk has not changed after implementing Basel III, and the liquidity is positively related to bank return (Table 4). It indicates that maintaining funding liquidity risk is incurring extra costs for banks in Bangladesh. Moreover, the results in Tables 3 and 4 reveal that the banks with a higher capital ratio take more liquidity risk and have a higher return.

Table 4: Determinants of bank return

VARIABLES	(1) ROA	(2) ROE
FGAP	1.4452**	22.9505***
	(0.5645)	(6.0716)
CAR	0.1335***	0.2538
	(0.0171)	(0.1791)
LNTA	-0.1489**	-2.4900***
	(0.0626)	(0.6833)
NIM	-1.3807***	-19.6369***
	(0.2093)	(2.4561)
NPL	-0.0161**	-0.2769***
	(0.0063)	(0.0755)
LLP/TL	-0.2129***	-2.1348***
	(0.0497)	(0.4855)
LA/TA	-0.0056	-0.1012**
	(0.0040)	(0.0467)
NL/TA	0.0095	0.1882***
	(0.0062)	(0.0645)
5Y_Bond	-0.0233	-0.1940
	(0.0148)	(0.1871)
GDP	-0.0154	-0.3071
	(0.0452)	(0.5446)
INF	-0.0299	-0.6352**
	(0.0271)	(0.3137)
2015-2019	-0.1221*	-1.1387
	(0.0727)	(0.8861)
Constant	3.1826***	58.2957***
	(0.9019)	(10.1260)

Observations	236	236
R-squared	0.5925	0.4456

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

1. Test of overidentifying restriction: H_o – instrument set is Valid and the model is correctly identified (Hansen's J, p = 0.2500), Test of endogeneity (orthogonality conditions) H_o – variables are exogenous (p = 0.0962), First-Stage Regression summary statistics: H_o – Instruments are weak (R-sq: 0.8893, Ad R-sq: 0.8807 and p = 0.000)
2. Test of overidentifying restriction: H_o – instrument set is Valid and the model is correctly identified (Hansen's J, p = 0.5553), Test of endogeneity (orthogonality conditions) H_o – variables are exogenous (p = 0.0416), First-Stage Regression summary statistics: H_o – Instruments are weak (R-sq: 0.8893, Ad R-sq: 0.8807 and p = 0.000)

6.2 Banks' cost efficiency and the effect of liquidity risk and bank capital on cost efficiency

Banks' cost efficiency has been examined following a two-step approach. The first step has examined how far cost-efficient the banks are, and their level of cost efficiency compare to the best performing bank in the sample. Then the second step examined the effect of liquidity risk and bank capital on this cost efficiency.

6.2.1 Cost efficiency of banks in terms of outputs and input prices

Q2a: How far cost-efficient are the banks?

It has been mentioned earlier that this study has applied three time-invariant and two time-variant SFA panel data models to disentangle time-invariant heterogeneity from time-variant inefficiency.

Table 5: Cost efficiency estimations

	(1) Fe (Within Group)	(2) RE (with Half normal distribution)	(3) RE (with Truncated Normal distributio n)	(4) True RE (with half-normal distribution)	(5) (True RE with Mundlak)
VARIABLES	Frontier	Frontier	Frontier	Frontier	Frontier

ln (Net loan/Total Assets)	0.0008**	0.0005*	0.0005*	0.0009***	0.0073*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0041)
ln (Securities/Total Assets)	0.0015***	0.0015***	0.0014***	0.0015***	0.0156***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0059)
ln (Other operating cost/Total Assets)	-0.0133**	-0.0169***	-0.0130**	-0.0147***	0.0988*
	(0.0060)	(0.0059)	(0.0054)	(0.0047)	(0.0505)
ln (staff cost/Total Assets)	-0.0113*	-0.0095	-0.0107*	-0.0114**	0.0058
	(0.0067)	(0.0066)	(0.0063)	(0.0050)	(0.0737)
ln (Net loan/Total Assets)^2					-0.0000
					(0.0000)
ln (Securities/Total Assets)^2					-0.0001**
					(0.0001)
ln (other operating costs/Total Assets)					0.0065
					(0.0049)
ln (Staff cost/Total Assets)^2					-0.0086
					(0.0092)
ln (Net loan/TA X Securities/Total Assets)					-0.0001**
					(0.0001)
ln (Net loan/TA X Staff Cost/Total Assets)					0.0002
					(0.0007)
ln (Net loan/Total Assets X other operating costs/Total Assets)					-0.0019***
					(0.0005)
ln (Securities/Total Assets X staff cost/Total Assets)					-0.0003
					(0.0009)
ln (Securities/Total Assets X other operating costs/Total Assets)					-0.0014*

					(0.0008)
ln (Staff cost/Total Assets X other operating costs/Total Assets)					0.0043
					(0.0103)
2015-2019	0.0227***	0.0233***	0.0234***	0.0196***	0.0187***
	(0.0023)	(0.0022)	(0.0023)	(0.0021)	(0.0023)
Constant	2.4438***	2.5375***	2.5508***	2.4536***	2.0873***
	(0.0280)	(0.0252)	(0.0352)	(0.0236)	(0.1869)
Observations	279	279	279	279	279
Number of ID	31	31	31	31	31

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5 presents the results of three time-invariant and two time-variant SFA panel models. It requires a certain interpretation of the stochastic terms to estimate the inefficiency of SFA models. It is commonly accepted in the literature that inefficiency is the skewed stochastic term with a certain distribution. As the SFA estimations have been conducted separately in this study to compute the efficiency scores, it has been assumed that the efficiency is not correlated with exogenous variables, and the idiosyncratic variations present symmetric error terms. Filippini et al. (2005) explained it as a legitimate and helpful estimation from a practical point of view. The correlation is generally positive as the banks' outputs increase the total cost. Hence, like most studies on cost efficiency mentioned here, this study has also found a strong positive relationship between the total cost and banks' outputs. Banks' outputs are highly significant across all the models applied, but the parameters are minimal. However, the estimations of time-variant models have provided a slightly upward-biased result. The coefficients of these models tend to be slightly higher than that of the unbiased estimation though the difference is minimal. Additionally, the efficiency estimations of the time-variant models show that the banks are nearly 99 per cent efficient, which is also not very realistic. The descriptive statistics (Table 1) show a difference in banks' total cost, input prices, and output data, which does not indicate that all banks are equally cost-efficient. Moreover, the year fixed effect results show that the bank cost between 2015 and 2019 is higher by 1.87 to 2.34 per cent across the specifications than in previous years.

The Hausman test has been conducted for the FE model; it suggests that the estimation of the FE model is unbiased; hence, it has been used as the benchmark estimation for other models. The coefficients of all the specified models are close to the coefficient of the FE model. The Random Effect models (Models 2, 3 and 4) assume that the heterogeneity term is uncorrelated to the explanatory variables, which is a shortcoming of these models. However, the Hausman test has proved that this assumption is not realistic for this study. The heterogeneity bias of these models has been further examined with Mundlak's (1978) auxiliary regression. The coefficients of this auxiliary equation (Table 5), with a linear combination of frontier parameters, show a small difference with the unbiased estimation except for the cost of capital. The results in Table 5 show that the auxiliary coefficients are also significant.

The multicollinearity and data heteroskedasticity issues have been explicitly considered for the SFA panel data models. Table 6 presents the multicollinearity and heteroskedasticity test results of the data applied in the first step. Panel A, in Table 6, shows the multicollinearity result via the Variation Inflation Factor (VIF). The VIF is an extended measure to analyse the presence of collinearity in a model, which was presented by Marquardt (1970). The VIF has been defined as –

$$VIF(\hat{\beta}_j, \hat{\beta}_{j0}) = \frac{var\left(\hat{\beta}_j\right)}{Var\,(\hat{\beta}_{j0}} = \frac{1}{1-R_j^2}$$

Where, $\hat{\beta}_j$is an estimator of $\hat{\beta}_j$, $\hat{\beta}_{j0}$ is the corresponding estimator with *j*th regressor orthogonal to the other explanatory variables in a model, and R_j^2 is the coefficient of determination, which results from regressing each *j*th variable on the rest of the exogenous variable/s. The value it provides is always higher than 1, as $0 \leq R_j^2 \leq 1$. Salmerón et al. (2015) stated that there might be different rules of thumb in the literature for accepting the existence of near multicollinearity. For instance, some scholars consider up to 10, and some consider up to 4 as no evidence of near multicollinearity.

Table 6: Heteroscedasticity and multicollinearity test results

	(1)
Panel A: VIF	
Loan/Total Assets	2.77
Securities/Total Assets	2.66
Other Operating cost/Total Assts	1.13

Staff cost/Total Assets	1.13
2015-2019	1.05
Mean VIF	1.75
Panel B: Breusch-Pagan test	
P-value	0.594
Observations	279

Here, the VIF test result validates no evidence of multicollinearity in the input costs and output data, as the VIF value of every exogenous variable is much lower than 4. Furthermore, panel B in Table 6 shows the Breusch-Pagan heteroskedasticity test result, showing that the data in the models is homogenous.

The cost efficiency estimations of banks, applying different models, have been provided as a descriptive summary in Table 7. The efficiency estimation of individual banks has not been provided here, as this study has focused on the efficiency of the entire industry and is not interested in disclosing the efficiency of an individual bank. The efficiency score computed by $\{-E(u|\varepsilon)\}$ is always positive, and it is 0 to 1, where 0 indicates not efficient at all and 1 means 100 per cent efficient. It simply shows the efficiency level of banks and helps to differentiate banks' excess costs, which an average bank could have achieved if it had functioned as competently as the sample's most efficient bank. The first three models are time-invariant, assuming that the efficiency is constant over time. The results in Table 7 show that the mean efficiency of time-invariant models is between 91 and 93 per cent, with a minimum of 87 to 89 per cent. The estimations show that a regular bank can save nearly 7 to 9 per cent of its cost on average if they operate as efficiently as the best-practising bank in the sample, which the literature defines as highly competitive.

On the other hand, models 4 and 5 have different stochastic terms and bank-specific heterogeneity. Auxiliary coefficients have mitigated the actual elasticity of model 5. The average efficiency estimations of these two models are nearly 99 per cent, which is not very realistic. However, no significant difference has been found in the efficiency estimation of state-owned and private banks in the country.

Table 7: Descriptive summary of technical efficiency estimations

Efficiency score exp{−E(u|ε)}	Model: 1 FE	Model: 2 RE (with normal-half-normal distribution)	Model: 3 RE (Truncated Normal distribution)	Model: 4 True RE (Half-normal distribution)	Model: 5 True RE with Mundlak's adjustment
Mean	0.9187	0.9278	0.9134	0.9869	0.9881
Minimum	0.8770	0.8863	0.8742	0.9197	0.9244
Maximum	1	0.9961	0.9862	0.9969	0.9966
Std. dev.	0.0289	0.0274	0.0272	0.0105	0.0091
N	279	279	279	279	279

6.2.2 Effect of liquidity risk and bank capital on cost efficiency

Q2b: What is the effect of liquidity on cost efficiency?

Q2c: What is the effect of bank capital on cost efficiency?

The cost efficiency scores of time-invariant models have been applied here as the dependent variables to examine their correlates in terms of Basel III key regulatory changes. As the efficiency estimates of time-variant models (models 4 and 5) are found slightly upward biased, they have not been applied in the IV GMM estimation to examine the determinants.

Table 8 presents the determinants of banks' cost efficiency in the country, and the relevant diagnostic tests have also been conducted to validate the instruments and models applied.

Table 8: Determinants of Cost efficiency (Dependent variables are the computed cost efficiency scores of FE, RE with normal-half-normal distribution, and RE with truncated normal distribution)

	(FE)	(RE with normal-half-normal distribution)	(RE with truncated normal distribution)
VARIABLES	Cost efficiency	Cost efficiency	Cost Efficiency

LA/TA	-0.0026***	-0.0034***	-0.0029***
	(0.0010)	(0.0011)	(0.0010)
LLP/TL	-0.0034**	-0.0036**	-0.0034**
	(0.0015)	(0.0018)	(0.0015)
LLR/TL	0.0002	-0.0004	-0.0002
	(0.0007)	(0.0008)	(0.0007)
NPL	-0.0003	-0.0006*	-0.0004*
	(0.0003)	(0.0003)	(0.0003)
CAR	-0.0022*	-0.0029**	-0.0025**
	(0.0012)	(0.0014)	(0.0012)
Log (TA)	0.0675***	0.0688***	0.0668***
	(0.0055)	(0.0064)	(0.0058)
MM R	0.0025***	0.0027***	0.0026***
	(0.0008)	(0.0010)	(0.0009)
INF	0.0011	0.0005	0.0007
	(0.0022)	(0.0027)	(0.0023)
LNGDPC	-0.0619***	-0.0668***	-0.0630***
	(0.0131)	(0.0151)	(0.0135)
Constant	0.5188***	0.5743***	0.5446***
	(0.1039)	(0.1221)	(0.1069)
Observations	259	259	259
R-squared	0.6087	0.3874	0.5198

Test of overidentifying restriction: Hansen's J, p = 0.8648, Test of endogeneity (orthogonality condition): H_0 Variables are exogenous, p = 0.000, First-stage regression: H_0 Instruments are weak, p= 0.0014

The results in table 8 show that cost efficiency is negatively related to banks' 'leverage ratio' (CAR). The elasticity of banks' cost efficiency and CAR is between 0.022 per cent and 0.029 per cent across the estimations; more explicitly, banks' cost efficiency decreases by 0.022 per cent to 0.029 per cent for every 1 per cent increase in the leverage ratio. This result is consistent with Altunbas et al. (2007); Fries and Taci (2004); Lin, Doan and Doong (2015); and LU et al. (2018). Altunbas et al. (2007) and Fries and Taci (2004) conducted their studies based on the European banking sector; Lin, Doan and Doong

(2016) conducted their study based on the 12 developing countries of Asia, and LU et al. (2018) conducted their study based on New Zealand banking sector. In addition, except for Fries and Taci (2004), all other studies have been conducted following a two-step approach. Table 9 shows the gradual increase in required bank capital in Bangladesh, and the results show that the increase in equity ratio reduces banks' cost efficiency or increases bank costs in the country.

Table 9: Phase-in Arrangement for Basel III implementation in Bangladesh

	2015	2016	2017	2018	2019
Capital Conservation Buffer	-	0.625%	1.250%	1.875%	2.500%
Minimum Common Equity Tier-1 plus Capital conservation buffer	4.500%	5.125%	5.750%	6.375%	7.00%
Minimum Tier-1 Capital Ratio	5.500%	5.500%	6.00%	6.00%	6.00%
Minimum Total capital plus Capital Conservation Buffer	10.00%	10.625%	11.250%	11.875%	12.500%
Revaluation reserve for fixed assets, Securities and Equity Securities	20.00%	40.00%	60.00%	80.00%	100.00%

(Data source: Bangladesh bank 2014)

The results in Table 8 show that bank liquidity is negatively related to banks' cost efficiency; the elasticity of cost efficiency and bank liquidity is between 0.026 per cent and 0.034 per cent across the estimations. In other words, banks' cost efficiency reduces by 0.026 per cent to 0.034 per cent when the liquidity increases by 1 per cent or liquidity risk decrease by 1 per cent. The literature shows that the increase in bank liquidity or decreasing liquidity risk may reduce cost efficiency through the term structure of interest rates and maturity mismatch. Figure 1 (Appendix) shows the changes in different interest rates after implementing Basel III. The Interest rate in the money market has been lowered evidently to curve this cost, but liquidity has been found to increase bank costs or reduce banks' cost efficiency. The findings of this study support the argument of Baker and Wurgler (2015) and Truck, Laub and Rachev (2004), who argued that increasing liquidity and capital requirements would increase bank costs or reduce banks' cost efficiency.

The results in Table 8 also show that the bank operation measured by LLP/TL is significantly related to cost efficiency. Some studies also define this control variable as an indication of credit risk. The cost efficiency of banks decreases by 0.034 per cent to 0.036 per cent against a 1 per cent increase in

LLP/TL. The bank size is the natural logarithm of the banks' Total Assets'. The results in Table 8 show that the bank size is positively associated, implying that the bigger banks are more cost-efficient in the country, which can be through the large production and lower unit cost of the loans.

Moreover, the macro-economic level variable 'Money market rate' and GDP changes in the country are significantly related to banks' cost efficiency. The interest rate in the money market, which is considered a regulatory mechanism, has been found to increase banks' cost efficiency or decrease bank costs. On the other hand, the GDPC has a strong positive effect on cost efficiency. The findings of these control variables are also consistent with the literature.

6.3 Effect of liquidity risk and bank capital on the growth of banks and NBFIs

This study has applied the pooled OLS and random effect models with relevant model selection and diagnostic tests to examine the growth of banks and NBFIs, and the differential impact on NBFIs. The regression results of Models 3.1, 3.2 and 3.3 have been presented in Tables 10, 11 and 12, accordingly showing and indicating the growth of banks and NBFIs and the differential impact on NBFIs with the treatment effect.

The results in Table 10 show the determinants of banks' loans and assets growth in the country. The growth in bank loans has been used as the main measure, and the growth in total assets has been used to support the main measure. The results show that banks' capital ratio is negatively related to banks' loan and assets growth, which means an increase in capital ratio decreases banks' growth in the country. The growth in banks' net loans decreases by approximately 0.975 per cent when the equity ratio increases by 1 per cent. Furthermore, Banks' credit risk controlled by LLP/TL is also negatively related to banks' growth. The results in Table 10 show that banks' growth in loans and assets decreases by 2.52 and 1.85 per cent, accordingly, when the LLP/TL increases by 1 per cent. On the other hand, banks' operational performance controlled by NIM is positively related. The growth in banks' loans and assets increases by 1.521 and 1.368 per cent, respectively, when the NIM increases by 1 per cent. The results further show that banks' loans and assets growth has decreased by 3.40 and 4.74 per cent after implementing Basel III in the country. The results in Table 10 also show that the inflation rate in the country is significantly and positively related to the growth of banks. However, the results show that banks' liquidity risk represented by LA/TA is not significantly related to banks' growth.

6.3.1 Effect of liquidity risk and bank capital on the growth of banks

Q3a: What is the effect of liquidity risk and bank capital on the growth of banks?

Table 10: Correlates of banks' lending and assets growth

	(1)	(2)
VARIABLES	Δ bank_loan	Δ Bank_TA
NIM	1.5214***	1.3679***
	(0.3791)	(0.2933)
LLP/TL	-2.5173***	-1.8542***
	(0.5236)	(0.3539)
LA/TA	-0.1503	0.0457
	(0.1000)	(0.0834)
CAR	-0.9726***	-1.0259***
	(0.3165)	(0.2337)
INF	2.3363***	4.2747***
	(0.7005)	(0.5439)
2015-19	-3.3950***	-4.7388***
	(1.2032)	(0.8951)
Constant	9.3447*	-5.0593
	(5.3754)	(3.9601)
Observations	246	246
R-squared	0.2058	0.4411

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Breusch and Pagan Lagrangian Multiplier (LM): P = 0.338 (Δ bank_loan) and P = 0.163 (Δ Bank_TA)

6.3.2 Correlates of NBFIs' growth and the differential impact on NBFIs

Q3b: Is there any differential effect of bank liquidity and banks' regulatory capital on NBFIs' growth?

Model 3.2 has been developed to examine the correlates of NBFIs' growth. Table 11 presents the impact of banks' required capital on NBFIs' growth; columns 1 and 3 of this table are the key estimations, and columns 2 and 4 are supportive estimates. In these estimations, banks' Required Capital Asset Ratio (RCAR) has been applied to examine the impact. The results show that the RCAR for banks has a significantly negative impact on the growth of NBFIs in the country. The RCAR is highly significant across all the estimations of NBFIs' growth. One of NBFIs' key fund sources is the banks' credit facilities. These results indicate that the increase in banks' required capital ratio decreases the provision of banks' credit supply to NBFIs, negatively affecting NBFIs' growth. The results in Table 11 also show that NBFIs' growth is positively related to their operation and credit risk. The results show that the growth in NBFIs loan share and total loan increased by 1.08 and 1.18 per cent when their NIM increased by 1 per cent. The results in Table 11 also show that the NBFIs' loan share increases by 0.45 per cent against a 1 per cent increase in LLP/TL, indicating the increase in credit risk increases the growth of NBFIs in the country. Furthermore, these estimations' year-fixed effect results show that there is no significant change in NBFIs' growth after implementing Basel III in the banking sector.

Table 11: Correlates of NBFIs' growth

	(1)	(2)	(3)	(4)
VARIABLES	Δ Loan share	Δ Market share	Δ Loan lease and advances	Δ Total assets
NIM	1.0844**	1.2782***	1.1827*	1.4395***
	(0.5336)	(0.4570)	(0.5999)	(0.5163)
LLP/TL	0.4579*	0.5305**	0.4797	0.5874**
	(0.2734)	(0.2338)	(0.3065)	(0.2655)
RCAR	-5.6588**	-12.1044***	-10.2093***	-14.0014***
	(2.5742)	(2.2604)	(2.8904)	(2.5282)
LA/TA	0.0945	-4.5811***	-1.9833	-4.4718**
	(1.8523)	(1.7288)	(2.0967)	(1.9193)
INF	1.6718	1.9441	2.9345	3.5578
	(2.2880)	(2.0978)	(2.5749)	(2.3776)
2015-19	2.0592	3.7549	5.0647	4.3464
	(6.4726)	(5.7549)	(7.3291)	(6.5084)
Constant	47.6209	168.3720***	124.9407***	189.3796***
	(41.8695)	(37.0394)	(46.5467)	(41.3477)
Observations	150	151	150	151
R-squared	0.0841	0.1493	0.1022	0.1777

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Breusch and Pagan Lagrangian Multiplier (LM): P = 0.1780 (Δ Loan share), P = 0.1646 (Δ Market share), P = 0.1819 (Δ Loan lease and advances), P = 0.1708 (Δ Total assets)

Table 12 presents the results of model 3.3 of the third objective, where the banks' and NBFIs' data have been combined. Columns 1 and 2 of this table show the determinants of both types of financial institutions' loan growth and market share. The difference-in-difference approach has been applied here to examine if the growth in loans and market share of NBFIs are significantly different from banks after implementing Basel III.

As banks and NBFIs follow different regulatory frameworks, and this study has focused on the differential impact of tighter regulation in the banking section, it has applied the RCAR to see the impact of required bank capital on both financial institutions. The results show that RCAR is highly significant and negatively related to the growth of banks and NBFIs' loan and market share. The difference-in-difference treatment effect shows that the growth rate in NBFIs' loan share over the entire sample period is significantly higher than banks, but the growth in loan share decreased significantly compared with banks after implementing Basel III.

Furthermore, the operational performance of both financial institutions is positively related to the growth in loans and market share. The results show that banks' and NBFIs' loan and market share increase by 1.10 and 1.26 per cent, respectively, when their net interest margin increases by one per cent.

Table 12: Growth in market and lending share of banks and NBFIs (with difference-in-difference treatment effect)

	(1)	(2)
VARIABLES	Δloan_share	ΔMarket_share
NIM	1.0316**	1.2409***
	(0.4455)	(0.3907)
LLP/TL	0.1953	0.2067
	(0.3178)	(0.2777)
RCAR	-2.3940*	-4.3167***
	(1.3668)	(1.1914)

LA/TA	-0.0915	-1.7837*
	(1.0530)	(0.9181)
INF	0.5670	1.0731
	(1.1186)	(0.9729)
1.2016-19	2.4668	1.5922
	(2.8724)	(2.5038)
1.NBFIs	5.8893**	1.0497
	(2.7224)	(2.3722)
1.2015-19X 1.NBFIs	-5.9858*	-0.4412
	(3.1067)	(2.6998)
Constant	19.7613	57.5874***
	(25.1558)	(21.9052)
Observations	396	397
Number of ID	50	50
R-squared (overall)	0.0674	0.0786

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Breusch and Pagan Lagrangian Multiplier (LM): P = 0.0431 (Δloan_share), 0.0399 (Δ Market_share)

Hausman: P = 0.9955 (Δloan_share), P = 0.9991 (Δ Market_share)

Banks' leverage ratio applied in model 3.1 and their required capital ratio applied in models 3.2 and 3.3 show that an increase in bank capital decreases the growth in lending and assets of both banks and NBFIs in Bangladesh. However, banks' liquid asset ratio is found to have no significant impact on the growth of banks and NBFIs. Furthermore, the correlation between the LLP/TL and banks and NBFIs' growth in lending and assets (Table 10 and 11) indicates that the NBFIs have an incentive to increase their credit risk, whereas it is the opposite for banks. The effect of bank capital and the difference-in-difference treatment effect results in Table 12 clearly indicates that the Basel III tighter capital ratio has decreased the growth of NBFIs in the country.

The findings on the determinants of banks' lending and assets growth (Table 10) underpin the findings of Roulet (2018). Based on the data of commercial banks in Europe, Roulet (2018) has shown that the growth in bank lending is negatively related to bank capital, and banks' lending growth has decreased significantly after implementing Basel III in European countries. This study also reinforces the assessment of the Financial Stability Board (2017), which assessed the evolution of shadow banking activities and the related financial instability risk they pose to G20 economies after the 2007-08 financial crisis. They have shown that the aspects of shadow banking that contributed to the crisis reduced significantly, no longer posed any instability risk, and recommended no regulatory action. On the other hand, the European Commission (2012) addressed that the risk of NBFIs magnifies when their size and interconnectedness with banks increase, and it may also arise from regulatory features. They said the larger the institutions involved, the bigger the risk of financial instability. Moreover, they also stated that it is unclear whether the burden of the growth rate in lending would lie with banks or private equity funds.

However, this finding differs from Irani et al. (2018) and Buchak et al. (2018), where both studies have shown that tighter regulation in the banking sector facilitates the growth of NBFIs in the USA. Irani et al. (2018) have shown that less capitalised banks decrease their loan retentions when required regulatory capital increases and capital is scarce; NBFIs step in to fill the gap. Buchak et al. (2018) have shown that the regulatory and technological differences between shadow banks and traditional banks have contributed to the growth of shadow banks' shares. They have also shown that tighter regulation in the banking sector accounts for almost 60 per cent of shadow banks' growth in the USA.

The multicollinearity and data heteroscedasticity has also been considered for these growth models. Table 13 demonstrates the multicollinearity test results of the variables applied via VIF. The way VIF checks multicollinearity in a data set has been detailed above. Furthermore, the robust standard error has been applied to avoid the issue of heteroskedasticity in the models applied.

Table 13: Multicollinearity test results for growth estimates with Variation Inflation Factor (VIF)

Panel A: VIF	(Δ $bank\_Lnand\_TA$) (2011-19)	(Δ *NBFIs_loan_market_share*) (2011-19)	(Δall *Loan_Market_share*) (2)
NBFIs			1.76
YEAR	1.44	3.02	3.68
NBFIS (treated)			2.79
CAR	1.34		
RCAR		3.14	3.05
LA/TA	1.31		1.03
LA/TA_Bank		5.83	5.88
Average			
INF	1.26	1.74	1.76

NIM	1.14	1.62	1.41
LLP/TL	1.10	1.58	1.35
Mean VIF	1.28	2.82	2.91

6.4 Robustness check

For the robustness check of the IV GMM models, this study has also tested the results with the pooled Ordinary Least Square (OLS) method. The instrumented variables have been excluded from the pooled OLS application as they are homogenous to instruments and the dependent variables, and applying instruments in the OLS will result in significantly high multicollinearity. The robust standard error cluster has been applied in the OLS regressions to control the heteroskedasticity. The application of pooled OLS to the models has also provided almost similar results.

For the robustness check of the cost efficiency results, this study has also applied individual year fixed effect in the SFA models and found that the cost was significantly higher in 2018 and 2019, indicating a long-term impact. Furthermore, along with the two-step approach, banks' cost efficiency and their determinants have also been examined following a one-step approach with True Random Effect (TRE) normal-half-normal distributions. It has been mentioned above that all the IV GMM models have also been estimated with lagged dependent variables. All the results are almost the same.

For the robustness check of the growth estimations, the random-effects model has been applied after the Hausman test for models 3.1 and 3.2 and pooled OLS for model 3.3. It has also checked the growth in the mortgage, corporate, and consumer loans of banks and NBFIs combined between 2015 and 2019 and applied cross-section fixed effects. All these different loans have been applied to check if the growth in NBFIs is higher in any type of loan market during the period mentioned. Furthermore, this study has adjusted the Consumer Price Index (CPI) with banks' and NBFIs' loan and assets data and calculated the real growth. The results of all alternative methods and different data sets are almost identical.

All the results for robustness check have been provided in the appendix section.

7. Conclusion and policy recommendations

7.1 Conclusion

This study aimed to identify the correlation between the liquidity risk and capital ratio and how they determine the bank return, cost efficiency, and the growth of banks and NBFIs in Bangladesh in terms of Basel III implementation. This study has applied the IV GMM to examine the correlation between liquidity risk and bank capital and to investigate their effect on bank return and cost efficiency. It has followed the SFA approach to estimate the efficiency scores and cost frontiers. Furthermore, this study has applied the pooled OLS and Random effect model with the difference-in-difference treatment effect to examine the growth of banks and NBFIs and the differential effect on NBFIs in the country. These methods have been applied separately to examine the objectives set for this study. This study has applied the data of 31 mainstream banks from 2011 to 2019, whereas the country started to adopt this regulation since 2015.

The results show that bank capital is negatively related to different types of funding liquidity risk; in other words, the banks with higher capital retain less liquidity and take a higher risk of funding liquidity. The results of the liquidity risk estimates are identical across all the measures applied. The liquidity risk is also correlated to bank operation and banks' credit risk, which has been controlled by banks' 'cost of fund', 'net Interest margin' and 'non-performing Loan ratio'. The year fixed effect results of the liquidity risk have shown that banks' level of liquidity risk has not changed significantly after implementing Basel III. Furthermore, the liquidity risk is found homogeneous to bank return and positively related, indicating the cost of liquidity risk. The leverage ratio is positively related to bank return which means banks with higher capital ratios have higher bank returns. Thus, the correlation of the capital ratio with liquidity risk and bank return reveals that the well-capitalised banks in the country take a higher liquidity risk and receive a higher return indicating the incentives of taking a higher risk of funding liquidity. However, the year fixed effect results show that the bank return has decreased significantly after Basel III implementation in the country.

Previous studies have shown that liquidity risk and bank capital are correlated, but they are limited to a specific measure of bank liquidity or a combined equation of many different types of bank liquidity. However, this study has shown the correlation between bank capital and liquidity risk with four different measures, extending the existing literature. Furthermore, it has followed a two-step approach to examine banks' cost efficiency. In the first step, the cost frontier and cost efficiency have been estimated with five different SFA panel data models, including three time-invariant and two time-variant models. The FE model developed by Schmidt and Sickles (1984) has been used as a benchmark estimation with the Hausman test for the alternative models to compare with. Then, it applied the estimated cost efficiency scores as explained variable to examine the effect of liquidity risk and bank capital. Both one and two-step approaches have been applied in the literature, but this study has applied the justified cost efficiency estimates of different panel SFA panel data models, unlike any other studies in the literature. This study has also shown that an unbiased and consistent cost-efficiency result can be derived through a comparative study of several SFA panel data models. Finally, the whole study has underpinned the findings of many studies conducted based on different countries.

The results show that bank cost has increased after implementing Basel III, and banks' outputs are positively related. The determinants of banks' cost efficiency have been examined with IV GMM in the second step, where the cost efficiency estimations have been derived from SFA panel data models. The efficiency estimations of time-invariant models have been applied to examine the determinants in the second step, as the efficiency estimations of time-variant models are slightly upward biased. It has been found in the second step that two key aspects of Basel III, bank liquidity and leverage ratio, are negatively related to cost efficiency, which means lowering liquidity risk and increasing leverage ratio reduces the cost efficiency or increases bank cost in the country.

The third objective of this study is to examine the growth of banks and NBFIs. The results show that the bank leverage and required capital assets ratios are negatively related to the growth of banks and NBFIs in the country. They are highly significant across all the key and supportive measures. Furthermore, banks' liquidity ratio is found to have no impact on the growth of financial institutions. The 'difference in difference' approach has shown that the lending growth of NBFIs is lower than banks after implementing Basel III, indicating lower credit supply from banks, which is one of NBFIs' key fund sources. The negative and highly significant impact of bank capital on the growth of banks and NBFIs indicates that banks reduce their credit supply when the required capital ratio increases. Thus, all the results indicate that implementing tighter regulation in the banking sector has not contributed to increasing NBFIs' growth nor increased the fragility in the country's financial market, which many scholars were concerned about.

This study has provided the country's regulators with significant insight. The well-capitalised banks have an incentive to take a higher risk of funding liquidity, so the regulators must monitor the funding liquidity risk of well-capitalised banks. This study has also shed light on explicit bank costs. It has been observed that the average interest rates on different term deposits increased after implementing this new regulation (Appendix: Figure 1). It has been argued that the term structure of interest rate and maturity mismatch are the key channels through which banks' liquidity risk may reduce banks' cost efficiency and returns. Thus, this study suggests that the regulators in Bangladesh must look into banks' investments, the cost of maturity mismatch and the cost of term structured interest rates. It has further been found that the increase in bank capital reduces cost efficiency, and the literature shows that an increase in bank capital significantly reduces the probability of a banking crisis. Here, the bank cost has increased by 1.87 to 2.34 per cent across the specifications, but the literature shows that the cost of a systemic crisis is much higher. It has also been argued in the literature that the increase in required bank capital would increase the growth of NBFIs and make the overall financial sector fragile through the spillover effect. However, this study has shown that tighter regulation in the banking sector has not increased the growth of NBFIs in the country. Thus, having all the results, this study recommends that the regulators strictly implement this Basel III liquidity and capital requirements. It has slightly reduced the cost-efficiency, but it will stabilise the sector in the long run, and the economic benefit will outpace the cost.

It has been explained above that Basel III regulatory changes were made in the wake of the 2007-2008 financial crisis, and it is seen as a "best practice" regulatory standard across the member countries as they are obliged to adopt and implement the recommended changes. Then, many non-member developing countries feel implicit pressure and are obliged to adopt Basel III standards even if the changes do not fit their needs for many reasons, including signalling to international investors, international expansion facilitating cross-border coordination, peer learning and peer pressure, and technical advice from the International Monetary Fund. The models applied in this study can directly be applied to all the developing countries that adopted Basel III capital and liquidity requirements. The liquidity risk, bank return, and cost efficiency measures of this study would address the level of liquidity risk different sized banks have and their return and cost efficiency in terms of Basel III key variables. Bank failure is rare in developing countries, but they often confront a systemic crisis that affects the entire economy. Applying these models would help the regulators identify the banks that pose a higher risk in the system. However, these models would not fit directly in developed economies as most of the developed economies have taken tighter measures in response to the 2007-2008 financial crisis along with Basel III: for example – Dodd-Frank Act (2010) in the USA, Financial Service Act (2013) in the UK, and Banking Union (2013) in the European Union. These regulatory changes were made intending to control the larger financial institutions that pose risks to the financial system.

Furthermore, these models are applicable t the financial sectors of India and Indonesia, two important economies in Asia. They both are Basel committee member countries and developing economies in many ways similar to Bangladesh. In Indonesia, the most common types of banks are commercial banks, and there are also foreign banks, Islamic banks, and some regional banks like the banking institutions in Bangladesh. In 2020, the banks held 86.9 per cent of the market share, while NBFIs held the remaining 13.1 per cent in the country. However, the NBFIs applied in this study are similar to non-bank finance companies in Indonesia, and the market share of non-bank finance companies was approximately 1 per cent in 2020, which is significantly small. Thus, the types of NBFIs applied in this study pose significantly less risk in the country's financial system by having a significantly small market share, so the comparative growth of banks and NBFIs may not be applicable in Indonesia.

On the other hand, there are similarities in the financial sectors of India and Bangladesh despite having a significant difference in the GDP size. India's banking sector consists of state, private and foreign-owned banks where the private banks hold a significant percentage of the market share like Bangladesh. There are also similarities in the nature and function of NBFIs in both countries. Like Bangladesh, the NBFIs in India include asset finance companies, Investment companies, Loan companies, Infrastructure finance companies, microfinance institutions, Gold loan companies, Housing finance companies, and Infrastructural debt funds. These institutions operate as a close substitute to banks and held nearly 15 per cent of the market share in 2021. Along with addressing the level of liquidity risk, bank return, and cost efficiency of different-sized banks in India, the comparative growth models of banks and NBFIs can also be applied to the country's financial sector. These models will show the growth of these two types of financial institutions after adopting Basel III. It would help the regulatory body to assess the level of risk different-sized banks and NBFIs pose to the financial system, which would help them to take preventative measures.

7.2 Policy Recommendations

It is a challenging task to predict a financial crisis with absolute certainty as it is a complex event and can be triggered by random shocks. However, there are some indicators that can indicate the possibility of a crisis. For instance, there were a set of developments before the last financial crisis, including a rapid increase in house prices in the 1990s, declining lending standards in the mortgage market and then a fall in house prices in mid-2006, causing the shadow banks' assets price to fall, and implicit regulatory safety net. Then the financial crisis was triggered by the rollover crisis and fire-sale of shadow banks' asset-backed securities (Christiano, Eichenbaum and Trabandt, 2018).

There are different tools and models that economists and policymakers use to identify the possibilities of a crisis. The models that the policymakers of major economies use are Dynamic Stochastic General Equilibrium (DSGE) models. DSGE models attempt to explain the behaviour of economies over time by incorporating explicit microeconomic foundations. The models assume that agents in the economy, like firms and households, make decisions based on rational expectations and that the economy is subject to random shock. These models use mathematical equations to explain the interaction between various agents in an economy. The stochastic aspect addresses the fact that changes are not entirely predictable and can be influenced by random shocks. These models generally consist of equations describing how different economic variables are determined by various factors (Christiano, Eichenbaum and Trabandt, 2018). DSGE models are used across many well-known policy-making boards, including the Board of Governance of the Federal Reserve System, the European Central Bank, the International Monetary Fund, the Bank of Canada, the Czech National Bank, the Sveriges Riksbank, and the Swiss National Bank; these policy institutions use these models in their policy-making process.

Based on this study's results, Bangladesh's regulatory authority can focus on the financial friction of the economy following the DSGE models developed by Gertler and Kiyotaki (2015) and Christiano, Motto, and Rostagno (2014). The pre-crisis DSGE models have been criticised for not predicting the crisis and addressing the financial system's vulnerability. Christiano, Eichenbaum and Trabandt (2018) explained that they did not emphasise financial friction. Then, they divided financial friction into two components; they are – i) friction originating inside the financial institutions and ii) friction originating from borrowers. Thus, based on the historical events and evidence, the regulatory body can adopt the rollover equilibrium developed by Gertler and Kiyotaki (2015) and the "risk shock" equilibrium by Christiano, Motto, and Rostagno (2014) as preventative measures to avoid future bank run that leads to a systemic crisis and sometimes bank failure. In the rollover equilibrium model, they showed that there is an equilibrium for a rollover crisis in shadow banking, but it can effectively be applied in both banking and non-banking sectors addressing the liquidity risk and trigger for a bank run. Furthermore, the "risk shock" equilibrium model assesses the level of riskiness of individual entrepreneurs or businesses. These models can be integrated into the system without significant complexity addressing the friction that originates inside the financial institutions and friction that might originate from borrowers. The rollover crisis and "risk shock" equilibrium models and their application in the country are detailed below.

The rollover crisis happens when the financial institutions cannot roll over their liabilities to the next period or depositors or creditors choose to withdraw their assets instead of rolling over to the following period. In Gertler and Kiyotaki's (2015) DSGE model, banks can rollover to the next period without any incident, and there is an equilibrium in which the creditors or depositors choose not to rollover to the next period, and they compared it to Diamond and Dybvig (1983) model of 'bank run'. In a rollover crisis, an individual creditor believes that other creditors will withdraw their credit and will not rollover to the next period. It leads to a system-wide bank failure and fire sales to pay off the bank debt that depletes bank equity. They considered the homogeneity of banks in their model and termed it as run on the banking system, and it causes fire sales as all banks sell their assets.

Gertler and Kiyotaki (2015) explained that the rollover crisis or run on the system could take place if the fire sales value of bank assets $(Z_t + Q_t^*)\ K_{t-1}^b$, is smaller than the outstanding liabilities, $R_t D_{t-1}$,. The condition for a bank run x_t equilibrium to exist is –

$$x_t = \frac{(Q_t^* + Z_t)K_{t-1}^b}{R_t D_{t-1}} < 1$$

Where x_t is bank run, $Q_t + Z_t^*)\ K_{t-1}^b$ is the liquidation or fire sales value of bank assets, and $R_t D_{t-1}$ is banks' outstanding liabilities.

Christiano, Eichenbaum and Trabandt (2018) later illustrated this model, explaining how a small shock can trigger a system-wide rollover crisis. Then they provided the following illustrative example of the model –

Pre-housing market correction		**Post-housing Market correction**	
Assets	Liabilities	Assets	Liabilities
120 (105)	100	110 (95)	100

The values in the parentheses are fire sales prices during a rollover crisis period. In the pre-housing market correction, if the value of the assets falls from 120 to 110, the system will still be solvent as the fire sales value is still 105. However, in the post-housing market correction, the liquidation value of the assets is 95, and the net worth is negative. Thus, this small change in asset price could lead to a bank run or rollover crisis in the whole system. Thus, this model could be used to calculate the probability of a bank run or rollover crisis, but it is conditional on the country's state of the economy.

This study shows that bank liquidity is negatively related to banks' Tier-1 capital meaning the increase in bank capital decreases banks' liquidity or increases liquidity risk, but it increases bank return. As the banks with higher capital take a higher liquidity risk and receive a higher return, the regulators are highly recommended to take preventative measures by regulating those banks following Gertler and Kiyotaki's (2015) DSGE model. The larger banks pose a higher risk in the financial system of an economy. The Dodd-Frank Act (2010) in the USA and the Vickers report (2011) in the UK have been implemented intending to control the larger banks as, historically, their bailout cost the public fund significantly. The regulators in the country are highly recommended to regulate the financial intermediaries' portfolio considering the fires sales and rollover crisis circumstances and maintain the rollover equilibrium as a preventative measure to avoid any future rollover or bank run crisis that might arise from having higher liquidity risk.

Along with the financial institutions' rollover crisis, the regulators are also recommended to emphasise the riskiness or risk level of the individual entrepreneurs or businesses. Christiano, Motto, and Rostagno (2014) showed that, during the last financial crisis, a large proportion of US business cycle fluctuation came from the riskiness of individual businesses, which they called "risk shock". Using many financial and macroeconomic variables in their DSGE model, they concluded that a significant part of GDP fluctuations came from the "risk shock" or the riskiness of businesses, and they developed an equilibrium for this "risk shock". They developed their model based on the following intuition –

In a recession, the borrowing cost increases; as a result, firms borrow less and demand for capital decreases. This decrease induces a decline in the price and quantity of capital. Then, this decline in investment leads to a decrease in production and an increase in bankruptcy, leading to an economywide recession. This recession also affects the stock market through the fall in capital prices and losses. Christiano, Motto, and Rostagno (2014) showed that shock to capital supply increases countercyclical movement in the stock market.

The regulators are recommended to adopt the following equilibrium developed by Christiano, Motto, and Rostagno (2014) to assess the riskiness of individual businesses and address the economy's vulnerability which can trigger a crisis or be triggered by a rollover crisis.

$$\overline{K}_{t+1} = \int_0^\infty \overline{K}_{t+1}^N f_t(N) dN.$$

Here, the equilibrium they mentioned is that the quantity of raw capital, $\overline{K}_{t+1}$, purchased by businesses over the period t must be equal to the quantity produced by the household, $\int_0^\infty \overline{K}_{t+1}^N f_t(N) dN$. They assumed that the larger the net worth of the businesses, the greater the resources available to the household. The regulators can focus on all different industries and equate their purchase of raw capital and productivity to address the level of risk they hold that can trigger or be triggered by a crisis.

It has been explained above how the credit market played an important role in the monetary policy transmission mechanism before, during, and after the crisis. For effective monetary policy in the country, the regulators can follow the DSGE model developed by Rubio (2020), which has shown that monetary policy is more effective with the financial accelerator, where the financial accelerator is borrowers' collateral constraints. They further demonstrated that the effectiveness decreased when the banks and banking regulations were added. This model has shown the equilibrium of outputs and inflation variability with the Keynesian model and added accelerator and banking variables. Thus, by applying this model, the regulators could know the role of this Basel III regulation in the effectiveness of the country's monetary policy.

The regulators must also consider the interest rate, the borrowers' indebtedness, asset price and bank capital for effective monetary policy. They can follow the DSGE model developed by Rubio and Yao (2015), which has shown that a low-interest rate environment in a stable period increase the indebtedness of household, leaving the borrowers exposed to credit risks when interest rate increases again. They then emphasised the active use of the countercyclical capital buffer of Basel III. They also implied the need for more aggressive capital requirement rules in a low-interest rate context to compensate for the risk. This DSGE model would complement the "risk shock" model developed by Christiano, Motto, and Rostagno' (2014), addressing the possibility of any future economic shock.

7.3 Limitation and further investigation

This study relied on the data from databases and NBFIs' annual reports. The common issues with developing countries are the quality of data collection and reporting systems, the level of regulatory oversight, and the transparency and accountability of the banking sector. In some cases, corruption or political interference can compromise the accuracy of banking data and provide incomplete, inaccurate, and manipulated data. Accurate data is the key to any research. The banking sector in Bangladesh is also criticised for poor governance and significant political influence. Thus, this study is limited to the data derived from the databases and annual reports; its effectiveness and accuracy depend on accurate data provision.

Further investigation can be conducted examining the change in banks' short- and long-term investments, demonstrating if banks' investments have moved significantly from long-term to short-term securities to comply with the new regulation. Furthermore, if the data is available, the change in the cost of maturity mismatch can also be examined. Lastly, more studies can be conducted showing the equilibriums for a bank run, risk shock environment, and effectiveness of the monetary policy adjusting banks and banking regulation in the economy following several DSGE models addressing the possibility of a future economic shock.

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Appendix

Figure: A1

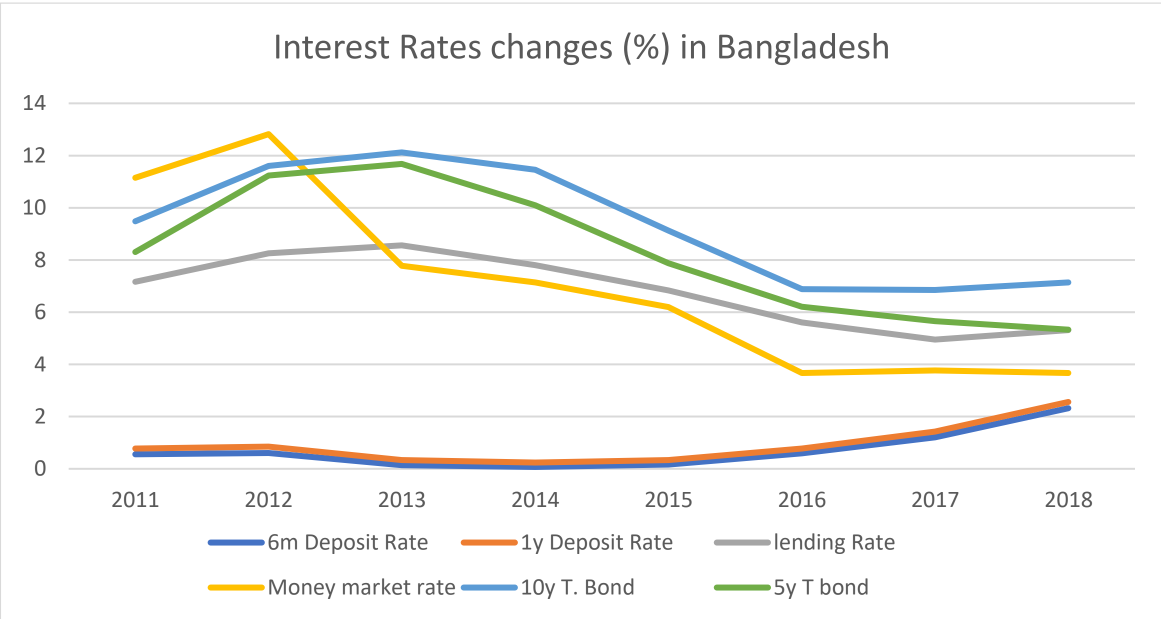


Table A1: Determinants of banks' liquidity risk with lagged (t-1) dependent variables using IV GMM

	(1)	(2)	(3)	(4)
VARIABLES	lag_FGAP(t-1)	lag_NetL/C&SF(t-1)	lag_LA/TA(t-1)	lag_NL/TA(t-1)
IE/TL	-0.0316*	3.5689*	-0.9344	2.7121*
	(0.0191)	(2.1190)	(1.1991)	(1.4363)
CAR	-0.0143***	1.4777***	-1.2962***	0.1271

	(0.0024)	(0.2825)	(0.1852)	(0.1985)
logTA	-0.0244	6.0993**	3.1740*	2.0804
	(0.0246)	(2.7210)	(1.6988)	(1.9285)
NIM	0.4166**	-38.7892*	-5.3782	-22.5843
	(0.1781)	(19.9771)	(11.3323)	(13.7563)
NPL	0.0051*	-0.6728*	0.1822	-0.6563***
	(0.0028)	(0.3636)	(0.1375)	(0.2536)
5Y_Bond	0.0110	-1.4018	0.4734	-1.2076
	(0.0102)	(1.1253)	(0.6312)	(0.7634)
LNGDPC	-0.3023***	28.9743***	-15.7362***	19.2873***
	(0.0602)	(6.9474)	(4.7308)	(4.9318)
INF	-0.0154	2.0322*	-1.0047	0.9429
	(0.0099)	(1.1896)	(0.7920)	(0.9146)
2015-2019	0.0157	-1.3071	-0.1702	-0.8041
	(0.0340)	(4.1497)	(2.6806)	(3.0033)
Constant	3.3345***	-286.3475***	135.6748***	-141.2615***
	(0.5748)	(67.3734)	(43.9809)	(52.5684)
Observations	212	213	212	213
R-squared	0.4356	0.3490	0.2690	0.3145

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A2: Determinants of banks' liquidity risk applying OLS with Robust cluster

	(1)	(2)	(3)	(4)
VARIABLES	FAGP	NetLoansDepSTFunding	LATA	NLTA
IETL	-0.0026	-1.1013	0.7060*	-0.1503
	(0.0056)	(0.6820)	(0.4141)	(0.5095)
CAR	-0.0139***	1.5238***	-1.3339***	0.1662
	(0.0023)	(0.2600)	(0.1719)	(0.1989)
logTA	0.0141	0.2807	4.5520***	-1.2687

	(0.0176)	(1.8438)	(1.3957)	(1.4549)
MIN	0.1431**	6.4077	-19.3330***	5.0866
	(0.0712)	(8.0011)	(4.6588)	(5.4570)
NPL	0.0065**	-0.8980**	0.3455**	-0.8025***
	(0.0028)	(0.3763)	(0.1538)	(0.2536)
YTBond	0.0091**	-0.6811	-0.2025	-0.6620
	(0.0045)	(0.5210)	(0.3539)	(0.4114)
logGDPC	-0.1437***	13.9374**	-11.8550***	10.2277**
	(0.0551)	(6.0961)	(4.3213)	(4.6762)
INF	0.0044	0.1916	-0.1855	-0.1729
	(0.0079)	(0.9061)	(0.6706)	(0.6850)
BM	-0.0034	-1.1273	-1.4373	0.1231
	(0.0310)	(3.4644)	(2.3173)	(2.4461)
Constant	1.1413**	-48.9558	76.2053*	-1.6708
	(0.5586)	(62.0848)	(44.1166)	(48.3062)
Observations	235	235	232	235
R-squared	0.4517	0.4309	0.3097	0.3758

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A3: Effect of liquidity risk and bank capital on bank return using lagged dependent variables with IV GMM

	(1)	(2)
VARIABLES	lag_ROA(t-1)	lag_ROE(t-1)
FGAP	1.7300**	30.8467***
	(0.7656)	(7.8476)
CAR	0.1205***	0.2834
	(0.0198)	(0.2135)
Log(TA)	-0.0142	-0.9911
	(0.1006)	(1.0879)
MIN	-1.2229***	-18.4636***

	(0.2263)	(2.5847)
NPL	-0.0248***	-0.4821***
	(0.0085)	(0.1345)
LLP/TL	-0.0429	-0.3890
	(0.0573)	(0.6035)
LA/TA	-0.0029	-0.0654
	(0.0049)	(0.0568)
NL/TA	0.0152**	0.2445***
	(0.0076)	(0.0800)
5YTBond	-0.0375*	-0.4068*
	(0.0195)	(0.2217)
GDP	0.1511**	2.0039**
	(0.0732)	(0.8245)
INF	0.1783***	1.2894**
	(0.0508)	(0.5083)
2015-2019	-0.3262**	-4.0692***
	(0.1320)	(1.4348)
Constant	-1.5943	4.4362
	(1.7631)	(18.0666)
Observations	206	206
R-squared	0.4704	0.3166

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Effect of liquidity risk and bank capital on bank return applying OLS with robust cluster

	(1)	(2)
VARIABLES	ROA	ROE
FGAP	0.6203	11.6658**
	(0.4271)	(4.5902)
CAR	0.1304***	0.2235
	(0.0159)	(0.1608)
LTA	-0.1650***	-2.7494***

	(0.0595)	(0.6647)
NIM	-1.1616***	-16.6079***
	(0.1903)	(2.2498)
NPL	-0.0166**	-0.2852***
	(0.0069)	(0.0782)
LLPTL	-0.2320***	-2.2384***
	(0.0499)	(0.4957)
NLTA	0.0051	0.1295**
	(0.0052)	(0.0566)
5Y_TBond	-0.0299	-0.1982
	(0.0199)	(0.2190)
GDP	-0.0104	-0.1447
	(0.0419)	(0.4994)
INF	-0.0136	-0.5299
	(0.0279)	(0.3218)
2015-2019	-0.1540*	-1.3947
	(0.0927)	(1.0213)
Constant	3.5760***	62.7826***
	(0.9419)	(10.5071)
Observations	239	239
R-squared	0.5995	0.4501

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A5: Determinants of cost-efficiency with lagged (t-1) dependent variables using IV GMM

	(1)	(2)	(3)
VARIABLES	lag_TE_fe	lag_te_pl81	lag_te_bc88
LA/TA	-0.0025**	-0.0033***	-0.0029**
	(0.0011)	(0.0013)	(0.0011)
LLP/TL	-0.0035**	-0.0043**	-0.0038**

	(0.0017)	(0.0021)	(0.0018)
LLR/TL	0.0003	-0.0001	0.0000
	(0.0007)	(0.0008)	(0.0007)
NPL	-0.0005*	-0.0007**	-0.0006**
	(0.0003)	(0.0003)	(0.0003)
CAR	-0.0018	-0.0025*	-0.0021*
	(0.0012)	(0.0014)	(0.0013)
Log (TA)	0.0690***	0.0710***	0.0688***
	(0.0056)	(0.0068)	(0.0061)
MM R	0.0025***	0.0029**	0.0026***
	(0.0009)	(0.0011)	(0.0010)
INF	0.0010	0.0006	0.0007
	(0.0021)	(0.0027)	(0.0023)
LNGDPC	-0.0601***	-0.0658***	-0.0620***
	(0.0129)	(0.0154)	(0.0136)
Constant	0.4752***	0.5291***	0.5018***
	(0.0997)	(0.1217)	(0.1052)
Observations	237	237	237
R-squared	0.6479	0.4041	0.5469

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A6: Growth in banks' lending and assets applying Random Effect model

	(1)	(2)
VARIABLES	Δ bank_loan	Δ Bank_TA
NIM	1.2490**	1.4273***
	(0.5652)	(0.4834)
LLP/TL	-4.3391***	-1.4939*
	(0.9418)	(0.7781)
LA/TA	-0.1327	0.0688
	(0.1191)	(0.1013)

CAR	-0.5194*	-0.9179***
	(0.3107)	(0.2655)
INF	2.4885***	3.9972***
	(0.7204)	(0.5877)
2015/19	-2.3100*	-4.0073***
	(1.3343)	(1.0918)
Constant	6.9489	-4.8318
	(5.8360)	(4.8209)
Observations	223	223
Number of ID	28	28
R-squared (overall)	0.2067	0.4201

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Hausman P = 0.3990 (Δ bank_loan) and P =0. 2127 (Δ Bank_TA)

Table A7: Correlates of all different loans growth originated by banks and NBFIs after 2015

VARIABLES	(1) Δmortgage_loan	(2) ΔConsumer_Loan	(3) Δcorporate_Loan	(4) ΔNet_Loan
CAR	-0.2218***	0.0345	-0.1200**	-0.0876***
	(0.0620)	(0.0506)	(0.0545)	(0.0149)
NBFIs	-0.0000	-0.1344	-0.0979	-0.0269
	(0.1142)	(0.0989)	(0.1117)	(0.0333)
Constant	1.5813***	0.0196	0.8691***	0.6617***
	(0.3816)	(0.3106)	(0.3330)	(0.0927)
Observations	160	168	140	228
Number of ID	40	42	35	57

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A8: Correlates of NBFIs' Growth

VARIABLES	(1) Δ Loan Share	(2) Δ Market Share	(3) Δ Loan lease and advances	(4) Δ Total Assets
NIM	0.9455	1.1388	1.3182*	1.2865
	(0.8688)	(0.7541)	(0.7796)	(0.8506)
LLP/TL	0.3905	0.4524	0.5419	0.5016
	(0.5438)	(0.4685)	(0.4838)	(0.5291)
LA/TA	0.1041	-4.5531**	-1.7187	-4.4413*
	(2.5731)	(2.2020)	(2.2729)	(2.4888)
RCAR	-5.7322*	-12.1470***	-8.7603***	-14.0485***
	(3.3894)	(2.8997)	(2.9992)	(3.2771)
INF	1.6102	1.9066	1.5048	3.5160
	(2.7470)	(2.3357)	(2.4307)	(2.6398)
2015-19	2.0634	3.7669	0.7813	4.3596
	(6.3629)	(5.4508)	(5.6389)	(6.1606)
Constant	49.2528	169.3178***	116.1890**	190.4281***
	(62.3340)	(53.2129)	(55.0876)	(60.1388)
Observations	150	151	149	151
Number of ID	19	19	19	19
R-squared (overall)	0.0839	0.1491	0.1388	0.1775

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Hausman P = 0.9920 (Δ Loan share), P = 0.9877 (Δ Market share), P = 0.9909 ((Δ Loan lease and advances), P = 0.9885 (Δ Total assets)

Table A9: Market and lending share of banks and NBFIs with difference in difference

VARIABLES	(1) Δloan_share	(2) ΔMarket_share
NIM	1.0978***	1.2609***
	(0.3508)	(0.2924)
LLP/TL	0.2248	0.2346

	(0.2806)	(0.2428)
RCAR	-2.3806**	-4.3223***
	(1.0638)	(1.0479)
LA/TA	-0.0924	-1.7917**
	(0.7718)	(0.7845)
INF	0.5680	1.0670
	(0.9935)	(0.8981)
1. 2015-19	2.4488	1.5636
	(2.1322)	(1.9223)
1.NBFIs	5.8355*	1.0255
	(3.1996)	(2.2915)
1.2015-19X1.NBFIs	-5.9745	-0.4253
	(3.9139)	(3.1690)
Constant	19.4181	57.7100***
	(18.0712)	(17.6477)
Observations	396	397
R-squared	0.0675	0.0786

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A10: Determinants of loans and assets grow of banks and NBFIs after adjusting CPI (2011 deflator)

	(1)	(2)	(3)	(4)
VARIABLES	ΔBank loan	Δ Bank assets	ΔNBFIs loan	Δ NBFI Assets
NIM	1.2478**	1.3831***	1.0498*	1.2803***
	(0.5296)	(0.4872)	(0.5748)	(0.4870)
LLP/TL	-3.8304***	-1.0740	0.3956	0.4864*

	(0.8851)	(0.8270)	(0.2951)	(0.2553)
CAR	-0.5002*	-0.8143***		
	(0.2940)	(0.2549)		
LA/TA	-0.0994	0.0829		
	(0.1096)	(0.0989)		
RCAR			-9.4631***	-13.0288***
			(2.7402)	(2.3923)
LA/TA_t			-0.9943	-3.1368*
			(1.7742)	(1.6376)
2015-2019	-3.2004**	-6.2015***	5.6275	4.8337
	(1.2457)	(1.0774)	(6.8951)	(6.1281)
Constant	15.6671***	14.1442***	117.1526***	179.2746***
	(3.7014)	(2.9037)	(44.8063)	(39.7365)
Observations	150	151	149	151
Number of ID	19	19	19	19
R-squared (overall)	0.0839	0.1491	0.1388	0.1775

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

A11: Cost efficiency estimate and the determinants using one step SFA approach.

	(1)	(2)
VARIABLES	Frontier	Mu
LA/TA		0.0021
		(0.0023)
LLP/TL		0.0152
		(0.0118)
LLR/TL		-0.0265**
		(0.0134)

NPL/TL		0.0016
		(0.0015)
CAR		0.0294***
		(0.0060)
LNTA		-0.5212***
		(0.0531)
MMR		-0.0146***
		(0.0038)
INF		0.0822***
		(0.0106)
LNGDPC		0.1369
		(0.1065)
ln (Staff cost/TA)	-0.0016	
	(0.0405)	
ln (Other operating cost/TA)	-0.0281	
	(0.0326)	
ln (Securities/TA)	0.0127***	
	(0.0026)	
ln (Net loan/TA)	0.0078**	
	(0.0031)	
Constant	12.4983***	6.8392
	(0.2069)	(0.0000)
Observations	259	259
Number of ID	31	31

List of banks taken as sample (from 2011 – 2019)

AB BANK LTD

AL-ARAFAH ISLAMI BANK LTD.

BANK ASIA LIMITED

BRAC BANK LIMITED

CITY BANK LTD

DHAKA BANK LIMITED

DUTCH-BANGLA BANK LIMITED

EASTERN BANK LIMITED

EXPORT IMPORT BANK OF BANGLADESH LIMITED

FIRST SECURITY ISLAMI BANK LIMITED

IFIC BANK LIMITED

ISLAMI BANK BANGLADESH LIMITED

JAMUNA BANK LTD

JANATA BANK LIMITED

MERCANTILE BANK LIMITED

MUTUAL TRUST BANK

NATIONAL BANK LIMITED

NATIONAL CREDIT AND COMMERCE BANK LIMITED

ONE BANK LIMITED

PREMIER BANK LTD (THE)

PRIME BANK LIMITED

PUBALI BANK LIMITED

RUPALI BANK LIMITED

SHAHJALAL ISLAMI BANK LTD

SOCIAL ISLAMI BANK LTD

SONALI BANK LIMITED

SOUTHEAST BANK LIMITED

STANDARD BANK LIMITED

TRUST BANK LTD (THE)

UNITED COMMERCIAL BANK LTD

UTTARA BANK LIMITED

List of NBFIs taken as sample

Bay Leasing and Investment Limited

Bd Finance

FAS Finance and Investment Limited

Firtst Lease Finance and Investment

Limited

GSP Finance

IDLC Finance Limited

IIDF Company Limited

IDCOL Limited

International Leasing and Financial

Services Limited

IPDC Bangladesh

Islamic Finance And Investment Ltd

LankaBangla Finance Limited

Midas Finance

National Housing Finance and

Investments Limited

Prime Finance and Investment

Union Capital

United Finance Limited

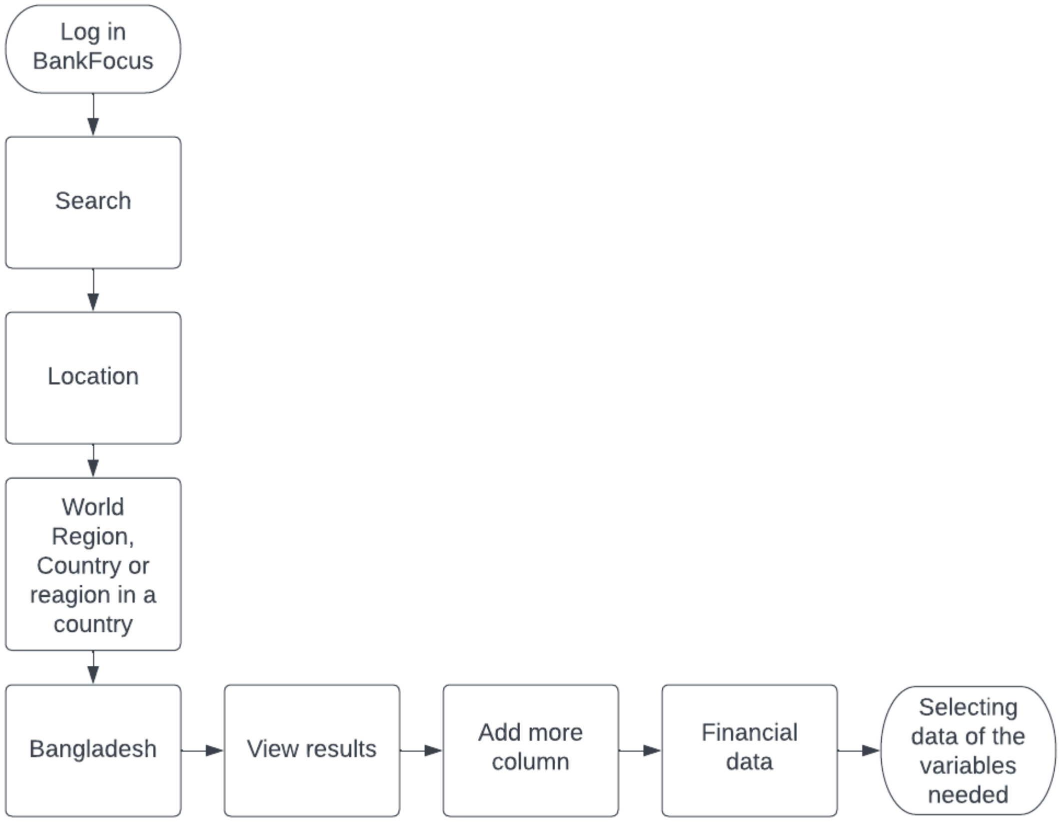
Uttara Finance and Investments

Delta Brac Housing Finance

All the equations and estimations have been conducted using the econometrics software STATA 16. All the commands are saved in 'Do' file and could be provided on request.

The process to download data from the Orbis BankFocus data base is given below.

How far has Basel III regulation affected the key banking sector variables in Bangladesh?



All the data has been cleaned and organised in MS Excel Sheet and uploaded to STATA for analysis.