

Three Essays on the United States Banking System

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Declaration of Co-Authorship

I am the sole author of Chapters 2 and 3 of this dissertation. I affirm that I have co-authored Chapter 1 with Dr. Michael Jones and Dr. Sharmila King. The nature of the co-authorship of Chapter 1 is outlined below.

Contribution to Chapter 1, titled: COVID-19, Non-Performing Loans and Monetary Policy: A Panel Data Investigation of US Community Banks.

The research topic was initially identified and developed by my coauthors, Dr. Michael Jonas and Dr. Sharmila King. I was responsible for framing research questions, constructing and cleaning the dataset, developing the empirical methodology, estimating the results, and preparing the first and subsequent drafts of the paper for journal submission. My coauthors, Dr. Michael Jonas and Dr. Sharmila King made significant contributions by writing the introduction and literature review, introducing new variables, and restructuring the methodology and results sections. They also reviewed and edited the chapter multiple times.

Abstract

The first chapter “COVID-19, Non-Performing Loans and Monetary Policy: A Panel Data Investigation of US Community Banks” co-authored with Dr. Michael Jonas and Dr. Sharmila King examined how each county in the US. had a disparate level of exposure to COVID-19 cases and subsequent government response; accordingly, the economic impact of the pandemic is expected to vary geographically. By combining geographically localized case levels with quarterly bank-level Call Report data, each bank’s balance sheet is linked with a county-specific level of per capita COVID-19 cases from 2019 Q1 to 2021Q1. Panel regressions are used to estimate the impact of COVID-19 on non-performing loans of US. community banks and find that midsize community banks in areas with higher COVID-19 cases experienced a statistically significant increase in aggregate non-performing loans. Findings indicate that local COVID-19 bank exposure significantly influenced expansionary monetary policy effectiveness as measured through Federal Reserve asset holdings which lowers the impact of COVID-19 on non-performing loans for community banks with assets less than \$500 million. Further division of NPLs of community banks into two main categories shows that except for the Commercial and Industrial NPLs category, all other NPLs are more sensitive to COVID-19 and monetary policy mitigation. The results suggest that small community banks with assets less than \$500 million show the effectiveness of the Federal Reserve asset purchases in mitigating the adverse effect of COVID-19 by reducing all other NPLs.

The second chapter “Examining the Effects of COVID-19 and Policy Responses on U.S. Commercial Bank Deposits” investigates why US commercial banks experienced a growth in deposits during the COVID-19 pandemic. Using the quarterly Call Reports of US. commercial banks, and county level data on COVID-19 cases, this study uses a panel approach which shows

that banks in US counties with a higher exposure to COVID-19 experienced a substantial increase in their deposits. When the study investigates the extent to which the Federal Reserve's monetary policy actions impacted the growth of bank deposits during the pandemic, the results show that it significantly contributed to the growth of bank deposits. While interest rate cuts played a role by encouraging savings through the deposit channel of monetary policy, results suggest that the effect of quantitative easing was more substantial in boosting bank deposits. Moreover, when banks are segregated according to asset size, the findings show that only small banks with assets less than 500 million experienced a surge in deposits mainly because these banks are considered less risky and more stable based on their conservative practices and have stronger relationship with their customers. In addition, the effect of COVID-19 cases on bank deposits also differs geographically. Due to pandemic disruptions leading to job losses and income reduction, the results show that banks located in rural areas experienced a smaller increase in their deposits as compared to their urban counterparts. Finally, this study clarifies the importance of bank capital and finds that small well-capitalized banks observed a surge in deposits during the pandemic because they are considered safe based on their conservative banking practices. The effect of expansionary monetary policy transmission is stronger on these banks because of their reliance on deposit funding, change in liquidity and strong customer relationship.

The final chapter “The Relationship Between Interest Rates and Bank Profitability: Evidence from a Dynamic Panel Threshold Analysis” explores the relationship between interest rates and bank profitability using a sample of 4031 US. commercial banks over the 2001Q1 – 2021Q1 period (or 326,480 bank-year observations). Specifically, I investigate the interest rate threshold effect in the interest rate – NIM nexus. To do so, this study applies a dynamic panel threshold regression model (DPTRM). The findings show that with the association between short

term interest rate and banks' NIM, the particular threshold value of short-term interest rate is 2.82%, determining the low and high-interest rate environments. In the low-interest rate environment, the bank's NIM decreases when the short-term interest rate decreases; however, in the high-interest rate environment, this value increases when short term interest rate decreases due to lower funding costs and increased loan demand. My findings also emphasize the importance of analyzing the distinct effects of interest rates on community and non-community banks, given their structural and strategic differences. Community banks, with their reliance on traditional lending and deposit-taking activities, exhibit greater sensitivity to interest rate changes, particularly in a low-interest rate environment. In contrast, non-community banks sustain NIM in both environments due to their diversified income sources and flexible funding strategies. This distinction underscores the importance of developing customized risk management strategies and policy approaches for these two banking segments to maintain profitability across different interest rate environments.

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“Seek knowledge even if you have to go as far as China.”

Prophet Muhammad (Peace be upon him)

This timeless Hadith has been a guiding light throughout my academic journey, reminding me that the pursuit of knowledge knows no boundaries. It captures the essence of perseverance, curiosity, and sacrifice that define the path to higher education. I wish to extend my deepest gratitude to all those whose support and guidance have made the completion of this PhD dissertation possible — a journey that has been both intellectually challenging and profoundly rewarding.

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Dedication

This dissertation is lovingly dedicated to my parents, Mr. Muhammad Azam and Mrs. Nuzhat Qureshi, whose endless love and sacrifices have guided me in every step of life; to my beloved husband, Syed Ghous Ali Shah, whose steadfast support and faith in me have been my greatest comfort; and to my brothers, Ammar Hameed and Ommair Hameed, whose encouragement and pride in my achievements have been a continuous source of motivation.

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Introduction

A well-functioning banking industry has long been recognized as a key component in ensuring growth and stability in developed economies (Bernanke, 2018). The U.S. banking system is one of the oldest, largest, and most important sectors of the overall economy. U.S. commercial banks play a central role in the functioning of the financial system and the broader economy. Serving as the primary intermediaries between savers and borrowers, they mobilize deposits, allocate credit, and manage risks that influence household welfare and firms' investment decisions (Diamond & Dybvig, 1986; Kashyap et al., 2002). Their balance sheets capture the transmission of monetary policy and financial market conditions, highlighting their role as an essential channel between the economy and the financial system (Bernanke & Blinder, 1990; Peek & Rosengren, 1995). However, disruptions in their balance sheets can amplify economic downturns and undermine policy effectiveness (Adrian & Shin, 2010; Brunnermeier & Sannikov, 2014). This dissertation contributes to the growing knowledge on banking and monetary policy by investigating questions on the dynamics of U.S. commercial banks to better assess financial stability and evaluate the effectiveness of monetary policy and its broader economic implications.

The thesis consists of three essays. In the essay co-authored with Dr. Michael Jonas and Dr. Sharmila King, we examined the impact of COVID-19 cases at the county level on the effectiveness of monetary policy in reducing U.S. community bank holdings of non-performing loans. In areas with higher levels of COVID-19 cases per capita, more businesses were forced to close or reduce operations, both due to the pandemic itself and government shelter-in-place orders. As business revenue and household incomes fell during this period, banks holding the debt of these entities saw an increase in the level of non-performing loans. The proportion of non-performing loans on a bank's balance sheet is an important indicator of health, both for the bank and its

borrowers. Previous studies (see Stiglitz & Weiss, 1981 and Peek & Rosengren, 2005) indicate that higher non-performing loans not only make it more difficult for borrowers to obtain credit as banks become more risk-averse but limit the bank's ability to issue new credit when bank capital is used to absorb non-performing loans. And, if banks provide additional loans to prevent existing borrowers from failing, funds are diverted from new, productive projects, creating a misallocation of resources (Balgova et al., 2018). Higher levels of non-performing loans in the banking system overall will therefore have a contractionary effect on the macro economy but these effects can be mitigated by the central bank through the lending channel of monetary transmission (Peek & Rosengren, 2000; Kashyap & Stein, 1995). Therefore, a major question that our analysis addresses is whether monetary policy was effective in influencing community bank's NPLs, and how the local exposure to COVID-19 influenced banks' sensitivity to expansionary policy. By combining geographically localized case levels with quarterly bank-level Call Report data, each bank's balance sheet is linked with a county-specific level of per capita COVID-19 cases from 2019 Q1 to 2021Q1. We use Hausman-Taylor panel approach to estimate the impact of COVID-19 cases at the county level on the effectiveness of monetary policy in reducing bank holdings of non-performing loans. Our findings indicate that midsize community banks in areas with higher COVID-19 cases experienced a statistically significant increase in aggregate non-performing loans. Moreover, our results show that expansionary monetary policy lowered the impact of COVID-19 on non-performing loans for community banks with assets less than \$500 million.

In the second essay, I focus on the liability side of the U.S. banks' balance sheets by using quarterly Call Reports of U.S. commercial banks, and county level data on COVID-19 cases to investigate why U.S. commercial banks experienced a growth in deposits during the COVID-19 pandemic. The existing literature (Baker et al., 2020 and Dong et al., 2021) indicate that during

the pandemic, households confronted drastic changes in economic and financial aspects of their lives. The pandemic not just affected economies but also financial institutions by changing the composition of bank balance sheets meaningfully. Earlier studies (see, e.g. Dursun-de Neef & Schandlbauer, 2020, 2022; Gatev et al., 2009; Gatev & Strahan, 2006) have shown that during crisis periods, depositors believe banks to be a safe place for their savings. Moreover, in response to the crisis period the Federal Reserve actions are designed to prevent a severe economic downturn by making credit more accessible to households and businesses (Cúrdia, 2020; Blank et al., 2020) where a surge in bank deposit inflows is an anticipated byproduct (Drechsler et al., 2024; Barr et al., 2020; Occhino, 2020; Drechsler et al., 2017). By employing a fixed effects panel approach, my results indicate that banks in U.S. counties with a higher exposure to COVID-19 experienced a substantial increase in their deposits as depositors believe banks to be a safe place for their savings. When the study investigates the extent to which the Federal Reserve's monetary policy actions impacted the growth of bank deposits during the pandemic, the results show that it significantly contributed to the growth of bank deposits. While interest rate cuts played a role by encouraging savings through the deposit channel of monetary policy, results suggest that the effect of quantitative easing is more substantial in boosting bank deposits.

The final essay reinvestigates the nonlinear relationship between interest rates and bank profitability by using a sample of 4031 US. commercial banks over the 2001Q1 – 2021Q1 period taken from Call Reports. In this study, I use net interest margin as a key source indicator of bank profitability. While previous studies on U.S. commercial banks (see, e.g. Bikker & Vervliet, 2018; Genay & Podjasek, 2014; Alessandri & Nelson, 2015) have established that the relationship between interest rates and net interest margins is nonlinear. However, they do not investigate whether there exists a regime-dependent threshold. Similarly, cross-county evidence (see, e.g.

Borio et al., 2017; Scheiber et al., 2016) supports the presence of nonlinear effects, showing that low-interest rate environments place disproportionate pressure on bank profitability. Yet only a limited number of cross-country studies (Claessens et al, 2018) formally estimates the relationship between interest rates and bank profitability which changes across different interest rate environments. However, despite the extensive literature on U.S. banking, no study to date has formally identify a specific threshold in the interest rate – net interest margin nexus. This chapter addresses this gap by applying the novel approach of dynamic panel threshold model developed by Seo & Shin (2016) which documents a threshold level of short-term interest rate to determine the low and high-interest rate environment to identify and quantify the nonlinear relationship between NIMs and short-term interest rates. My findings indicate that there exists a nonlinear relationship between short term interest rate and banks' NIM. Particularly, the threshold value of short-term interest rate is 2.82%, determining the low and high-interest rate environments. Further, this study is the first to investigate the interest rate threshold effects on NIM for both community and non-community banks in the US. It provides novel insights into the nonlinear relationship between interest rates and NIM across these distinct banking segments, addressing a critical gap in the literature. My results show that community banks, with their reliance on traditional lending and deposit-taking activities, exhibit greater sensitivity to interest rate changes as compared to non-community banks, particularly in a low-interest rate environment.

The findings in this thesis contribute to a deeper understanding of the role of commercial banks in the economy and the transmission of monetary policy. By offering evidence on how banks adjust their balance sheets and performance in response to changing economic and policy environments, this research provides insights that are relevant for academics, regulators, and policymakers concerned with financial stability and sustainable economic growth.

1. COVID-19, Non-Performing Loans and Monetary Policy: A Panel Data Investigation of US Community Banks

1.1 Introduction

The degree of exposure to COVID-19 cases varied widely across geographic locations within the US throughout 2020. The impact of the pandemic not just affected the non-performing loans (NPLs) of all banks but also presented unique challenges to community banks. Community banks faced particular difficulties due to their closer ties to the local communities that were hit hard by the pandemic. In this paper, we combine county-level COVID-19 case values with a quarterly panel dataset of community bank balance-sheets to investigate how variation in non-performing loans (NPL's) relates to localized severity of the pandemic among different size categories of community banks, as well as how COVID-19 severity influenced the efficacy of the monetary policy response. In areas with higher levels of COVID-19 cases per capita, more businesses were forced to close or reduce operations, both due to the pandemic itself and government shelter-in-place orders. As business revenue and household incomes fell during this period, banks holding the debt of these entities would likely see an increase in the level of distressed or non-performing loans. This effect will likely have been offset to some degree by federal and state government pandemic-related relief efforts (Payment Protection Program, CARES Act, etc.). Expansionary monetary policy came in the form of reducing the federal funds rate and an expansion of the Federal Reserve asset purchases under quantitative easing. While these efforts had the intended effect of reducing borrowing costs and increasing liquidity, we find that the impact on community banks balance sheet varied by bank size and degree of COVID-19 exposure in the banks' area of operations.

The proportion of NPL on a bank's balance sheet is an important indicator of health, both for the bank and its borrowers. NPLs are defined as loans with repayments that are more than one month overdue, or in default. Although NPLs may have originated as any type of loan (commercial and industrial, personal, or real estate loans) the impact on the bank will be the same: lower equity, lower levels of interest revenue, and a decreased amount of funds available to generate new loans. However, the size and type of NPLs help determine the extent of their impact on a bank's financial health. Credit availability is important for business expansion and to finance daily operations. Higher NPLs not only make it more difficult for borrowers to obtain credit as banks become more risk-averse but limit the bank's ability to issue new credit when bank capital is used to absorb NPLs (Stiglitz & Weiss, 1981; Peek & Rosengren, 2005). And, if banks provide additional loans to prevent existing borrowers from failing (zombie lending), funds are diverted from new, productive projects, creating a misallocation of resources (Balgova et al., 2018). Higher levels of NPL's in the banking system overall will therefore have a contractionary effect on the macro economy but these effects can be mitigated by the central bank through the lending channel of monetary transmission (Peek & Rosengren, 2000; Kashyap & Stein, 1995).

Since our paper focuses on US community banks which are small to medium-sized financial institutions that emphasize personalized banking services and local decision-making to cater primarily to the needs of their surrounding communities. They stand out for their strong community involvement, offering tailored financial solutions to individuals, small businesses, and local agricultural entities. These banks are characterized by their close customer relationships, flexibility in providing services, and significant contributions to local economic development. Operating under the regulation of federal and state agencies, community banks face unique challenges such as competition from larger entities and adapting to digital innovations, yet their

deep-rooted understanding of local markets positions make them a good fit to navigate these challenges and continue playing a crucial role in the financial ecosystem.

Now the question about the mechanism by which the COVID-19 pandemic likely influenced community banks' holdings of non-performing loans is twofold. First, and most obviously, lockdown policies forced businesses to reduce or halt operations. This temporary drop in aggregate demand decreased wage income for households, and revenue streams for firms, making them more likely to default on loans. Second, the macroeconomic uncertainty and financial market volatility created by the pandemic made alternative sources of funding for firms more difficult to obtain, leading to a reliance on debt and bank-loans funding for struggling firms. Community banks, which often serve as the financial backbone of local economies, were particularly vulnerable to these shifts due to their close ties to the local businesses and populations that were most affected. Therefore, a first important hypothesis which our analysis tests is whether U.S. community banks faced a significant crisis, particularly concerning non-performing loans (NPLs) with a rise in per capita COVID-19 cases. Banks which we expect to be most affected within areas of high COVID-19 cases are those with the least amount of diversification of the loan portfolio, and with customers least able to take advantage of government stimulus programs. We hypothesize that regional and community banks, and banks located in rural areas will have a less diverse portfolio of borrowers and therefore be more susceptible to the impact of COVID-19.

A second major question that our analysis addresses is whether monetary policy was effective in mitigating the adverse impact of COVID-19 on community banks' NPLs. Expansionary monetary policy can have an influence on community banks' NPLs by creating an environment that reduced the likelihood of loan defaults. Using the federal funds rate as a traditional measure of policy stance as well as the growth in assets held by the Federal Reserve to

represent quantitative easing, we find that for small bank size categories, operating in high-COVID-19 areas, the Fed's policy helped reduce the impact of the pandemic on banks' holdings of NPLs.

Among other types of loans, community banks issue commercial and industrial (C&I) loans. Economic downturn and crises can influence the amount of C&I lending. Therefore, community banks tend to reduce the issuance of C&I loans when there is more credit risk. These banks will adopt policies and procedures to reduce their risk exposure associated with C&I lending during the crisis period.¹ During the COVID-19 pandemic, stress tests were used to determine the banks' potential to provide liquidity. Evidence suggests that C&I lending expanded rapidly for larger banks with asset size more than \$50 billion as a result of large credit line drawdowns by large firms.² Another area where community banks mainly lend is in commercial real estate (CRE). Throughout the US, CRE lending is an essential operation undertaken by both large and small banks.³ The three major categories of CRE loans are loans secured for the acquisition, construction, and development of real estate (C&D); nonfarm, non-residential properties; and loans secured by multifamily properties. Community banks have served as key CRE credit providers across markets of varying sizes and are remarkably dominant in smaller communities. Community banks located in rural regions and small urban areas hold a large portion of CRE loans based on Call Report data. The COVID-19 crisis significantly reshapes the structure of CRE markets in the US. Overall, CRE market downturn was reflected in the deteriorating credit performance of portfolios of CRE loans. Credit quality worsened as financial pressure due to the pandemic increased commercial property

¹ <https://www.communitybankingconnections.org/articles/2012/q4/sound-risk-management-practices-in-community-bank-ci-lending>

² For press accounts, see "Banks tolerate credit-line draws in coronavirus crisis — for now," American Banker, March 26, 2020, and "Credit-line drawdowns have peaked. Will banks get repaid?" American Banker, April 15, 2020.

³ www.fdic.gov/resources/community-banking/report/2020/2020-cbi-study-4.pdf

vacancy rates, reduced property financial flows, therefore hindering repayment of loans. Our paper divides NPLs into two main categories, commercial and industrial NPLs (C&I NPLs) and all other NPLs to investigate the effect of COVID-19 cases per capita and how effectiveness of monetary policy helps to mitigate the pandemic effects on the two categories of NPLs.⁴

The limited literature on U.S. community banks, particularly in the context of non-performing loans (NPLs) during the COVID-19 pandemic, highlights a gap in academic and financial research. This insufficient detailed analysis is attributable to the distinctive role of community banks in the broader banking sector where much of the banking literature tends to concentrate on larger banks. The contribution of this research aims to encourage more scholarly attention to community banks and their resilience in the face of pandemic which can help community banks to handle future economic crisis.

Our study is related to Beck & Keil (2022) who find that banks with greater geographical exposure to the pandemic and lockdown measures experienced an uptick in non-performing loans. Using the sample data of at most 46,591 bank observations from the period 2019Q1 to 2021Q1, we address potential endogeneity with respect to bank-specific time-invariant errors using the Hausman-Taylor panel estimator. We control for state-level government assistance and fixed effects, as well as county-level demographic and economic indicators to investigate the impact of COVID-19 cases at the county level on bank holdings of non-performing loans which differs from the study of Beck & Keil (2022) in a few important ways. First, while Beck and Keil (2022) analyze the impact of COVID-19 on all US commercial banks, this study focuses specifically on community banks. This distinction is important because community banks are more locally

⁴ All other NPLs: Commercial Real Estate (single family, multi-family, non-farm residential, construction and land development, and farmland), Individual (Credit Card, Auto, other), and Farm lending.

oriented and rely heavily on relationship lending, making them particularly suitable for analyzing the effects of COVID-19 as a localized shock to give more attention to the importance of these banks and their resilience during the pandemic. Second, this paper incorporates lending channel of monetary policy to examine whether it remained effective in reducing community banks' NPLs, and how the local exposure to COVID-19 influenced banks' sensitivity to expansionary policy. Although the lending channel has been widely studied in the literature, its functioning under pandemic conditions remains relatively underexplored and is not addressed by Beck and Keil (2022). Finally, this study contributes by disaggregating NPLs into two main loan categories, commercial and industrial NPLs (C&I NPLs) and all other NPLs to investigate in which category local exposures to COVID-19 was more influential on banks' sensitivity to expansionary policy.⁵ In contrast, Beck and Keil, focus on aggregate measure of bank balance sheet health and do not examine heterogeneity across different categories of NPLs.

The rest of the paper is organized as follows: section 2 provides review of the literature on NPLs, the COVID-19 pandemic and monetary policy; section 3 reports the data description; section 4 presents the empirical model and its specifications; section 5 outlines the results; and section 6 concludes.

1.2 Literature Review

Our paper combines and expands on several strands of the existing literature on banking and monetary policy, to show not only that the COVID-19 pandemic represented a real economic shock to the US community banks, but also measuring the degree to which the Federal Reserve policy was able to insulate balance-sheets of these affected banks. Using a similar bank branch-

⁵ Commercial Real Estate (single family, multi-family, non-farm residential, construction and land development, and farmland), Individual (Credit Card, Auto, other), and farm lending.

county level geographic COVID-19 exposure measure to ours, Beck & Keil (2022) find that banks that had more geographic vulnerability to pandemic related measures were associated with an increase in loss provisions and/or non-performing loans.

There is a growing literature examining the reaction of banking systems to various elements of the COVID-19 pandemic - geographically proximate caseloads, local lockdown policies, as well as availability of government stimulus and lending. Greenwald et al. (2020) and Dursun-de Neef & Schandlbauer (2020) show that commercial lending increased at the onset of the pandemic. Both Acharya & Steffen (2020) and Chodorow-Reich et al. (2022) findings suggest the bulk of increased lending comprised a substantial drawdown of bank credit lines by large firms in the immediate aftermath of the pandemic onset putting pressure on bank balance sheets.⁶ Banks accommodated this unprecedented liquidity demand from firms through use of cash inflows from depositors as well as Federal Reserve interventions in the repo market and bank capital (Li et al., 2020). Banks that experienced large credit-line drawdowns reduced the supply of new loans (Acharya et al., 2021) and specifically reduced lending to small firms (Greenwald et al., 2020).

A contributing factor to the reaction of firms' demand for credit from the banking sector to COVID-19 was the Paycheck Protection Program (PPP), a government backed small-business lending program that operated through May 2021. Li & Strahan (2021) show that the timing of PPP lending depended on the strength of the lender-borrower relationship. Granja et al. (2022) find an inverse relationship between the quantity of early PPP funding received and proximity to local COVID-19 exposure.

⁶ These credit line drawdowns exceeded \$500bn (Li et al., 2020)

Our research question directly addresses the strength of counter-cyclical monetary policy in mitigating the effect of the COVID-19 crisis on bank balance sheet weakness represented by non-performing loans (NPL). Ari et al. (2020) use historical data to show that NPLs play a critical role in propagating and recovering from crises and recessions and predict a similar role in the current scenario. Kasinger et al. (2021) highlight the importance of early diagnosis of an NPL problem at the bank-level, and the potentially important role of secondary loan markets to resolve the issue.

Dursun-de Neef and Schandlbauer (2020) find that insured bank deposits increased.⁷ Banks also increased their cash holdings. We would expect that the lending channel of a monetary expansion, in the aftermath of the crisis, would cause the supply of bank loans to increase as banks adjust their portfolio to accommodate the influx of reserves (Bernanke & Blinder, 1988; Kashyap & Stein, 1995, among others). This occurs due to the increased availability of non-borrowed reserves in the federal funds market as well as the discount window and asset purchases during the current era of quantitative easing. However, the central bank's ability to shield the economy from an exogenous public health shock, can be hampered by a shift in banks' behavior as uncertainty and increasing imperfect information forces a bank to ration credit and tighten credit standards (Castro et al., 2022; Stiglitz & Weiss, 1981).

There is limited literature which examines the performance of community banks in the US during the COVID-19 pandemic. Hassan et.al (2022) evaluate the outcomes of COVID-19 on the financial performance of community and large banks and find that community banks significantly perform better than large banks based on their ability to maintain strong customer relationships

⁷ While they attribute this to a flight to safety, it could also be the drop in aggregate demand due to lockdowns early in the pandemic and the deposit of stimulus checks in December 2020.

and better knowledge of local businesses amid the pandemic period. They also find that the community banks' performance differed regionally during the COVID-19 pandemic. Kwan (2021) assessed the resilience of community banks on the onset of the pandemic and find that for small community banks the risk of bank insolvency leading to bank instability is small during crisis period.

1.3 Data and Descriptive Statistics

1.3.1 COVID-19 and County-level Data

COVID-19 data comprises of daily data on the number of confirmed cases for each county in US and taken from the Center for Systems Science and Engineering (CSSE).⁸ We followed Beck and Keil (2022) to measure bank-specific exposure to COVID-19 case count. We derive the average exposure to regions in which the bank is physically present, using 2019 bank branch deposit shares in total bank deposits as weights for each county (based on Federal Deposit Insurance Corporation's Summary of Deposits data). Thus, the treatment variable is the logarithm of bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county.⁹ Figure 1.1 shows differences in COVID-19 case exposure across states. While Figure 1.2 depicts differences in nonperforming loans (NPLs) as a ratio of total assets across states.

⁸ Number of confirmed COVID-19 cases for each U.S. county starts on January 22, 2020.

⁹ In order to handle zero COVID cases, COVID-19 exposure is calculated as logarithm of 1 + the bank level exposure to COVID cases.

Figure 1.1: Confirmed COVID-19 Cases by State, 2021

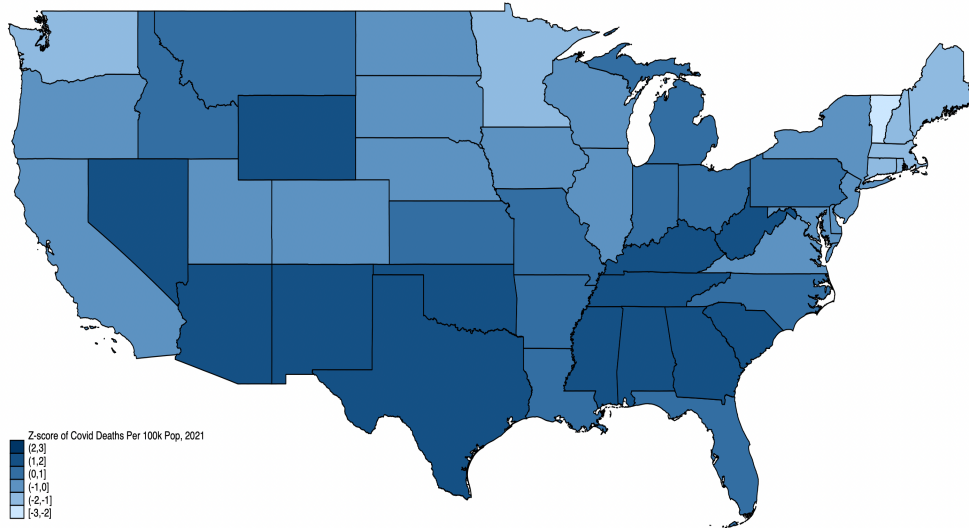
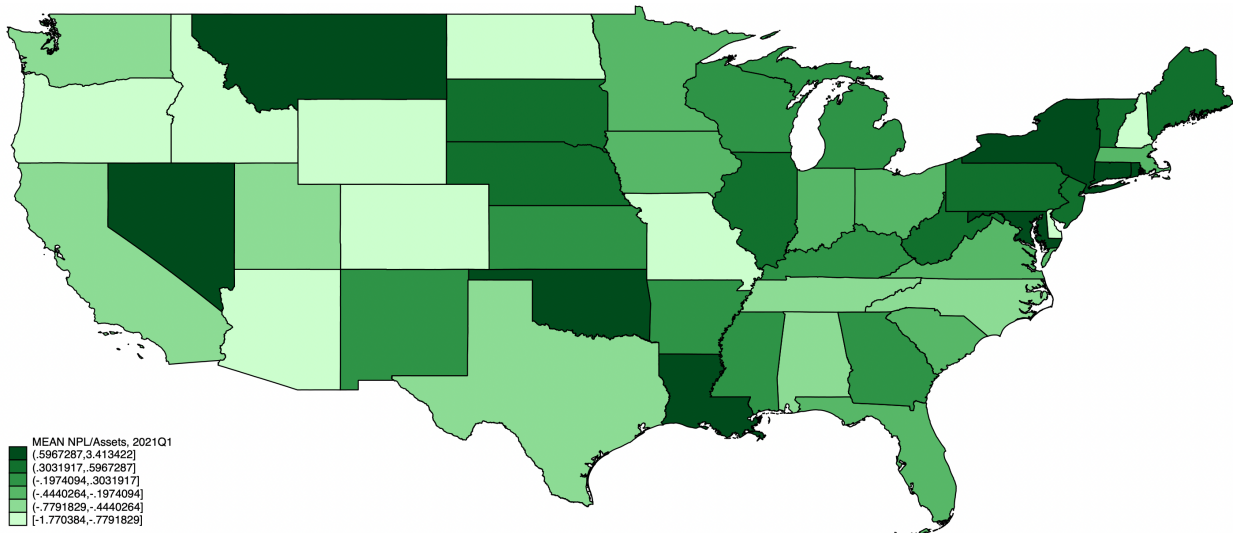


Figure 1.2: NPL/Assets Mean by State, 2021Q1



In addition to the COVID-19 measures, our data contains county-level demographic controls variables. These include population, population density and a rural-urban indicator. The rural-urban indicator is defined at the county level, ranging from 0 to 8 where higher values indicate increasingly rural the counties.

1.3.2 Bank Data

We use quarterly Call Reports submitted by all FDIC-insured commercial banks with the Federal Financial Institutions Examinations Council (FFIEC) as a primary source of bank data, for the period 2019Q1 to 2021Q1.¹⁰ We are limiting our examination to the four quarters prior to the start of the pandemic and four quarters after the onset. The quarterly data of the cross-sectional bank balance-sheet is an unbalanced panel data from the period 2019Q1 to 2021Q1. The variable list can be found in the appendix, and Table 1.1 reports the summary statistics for the main variables used in the analysis. In total, the sample comprises at most 46,617 bank observations (based on 5180 banks over 9 quarters).

Table 1.1 shows the mean balance sheet ratios for all community bank quarters from 2019Q1 - 2021Q1. On average, community bank in our sample has \$6.09 million in total assets. The mean ratio of total equity to total assets is 12%. The average bank's return on assets is 0.8%, while net interest income represents 2.6% of assets. According to our sample banks primarily fund their assets through deposits which account for 83% of their liabilities. As Figure 1.3 shows, NPLs in general, represent a small percentage of a bank's balance sheet.

¹⁰ Vaccine rollout begins March 2021; however, vaccine uptake varies across the nation. <https://www.cdc.gov/museum/timeline/covid19.html>

Table 1.1: Summary Statistics for all Community Banks from 2019Q1 – 2021Q1

Variables	Mean	Std. Dev.	Min	Max	N
Bank-Level Data					
Assets (000's)	609,757.9	1,137,257	3408	9,989,803	44,844
Total Deposits/Assets	0.832	0.092	0.0003	0.983	44,844
Equity/Assets	0.123	0.070	0.006	0.992	44,810
Non-Performing Loans/Assets	0.005	0.008	0	0.188	39,685
Net Income/Assets	0.008	0.040	-0.271	3.978	39,694
Interest Income/Assets	0.026	0.014	0	0.233	39,694
Log (Assets)	12.477	1.242	8.134	16.117	44,844
Bank level Employment	99.886	184.47	0	5031	39,694
County-Level Data					
COVID cases	10,589.06	53,597.39	0	1,219,614	45,632
Log (COVID cases)	3.892	4.144	0	14.014	45,632
Log (COVID cases per capita) (weighted Population	3.817	3.914	0	10.855	45,652
Population	455,703.5	1,207,894	431	10,000,000	46,399
Population Density	525.741	1794.597	0	17995.9	46,106
Rural-Urban Indicator	2.895	2.616	0	8	45,033
Macro-Level Data					
Fed Funds Rate	1.157	1.003	0.06	2.403	46,165
Log (Fed Assets Purchase)	15.452	0.288	15.149	15.833	46,165
Fiscal Stimulus	2,090,415	5,679,668	0	43,500,000	46,590
Unemployment Rate	5.877	3.058	3.533	13.033	46,115

Figure 1.3: NPL/Assets Frequency Diagram (All Banks, 2019Q1-2021Q1)

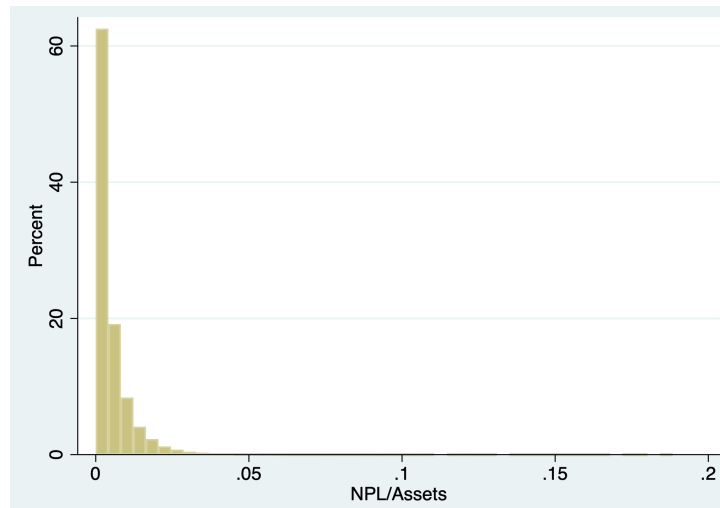
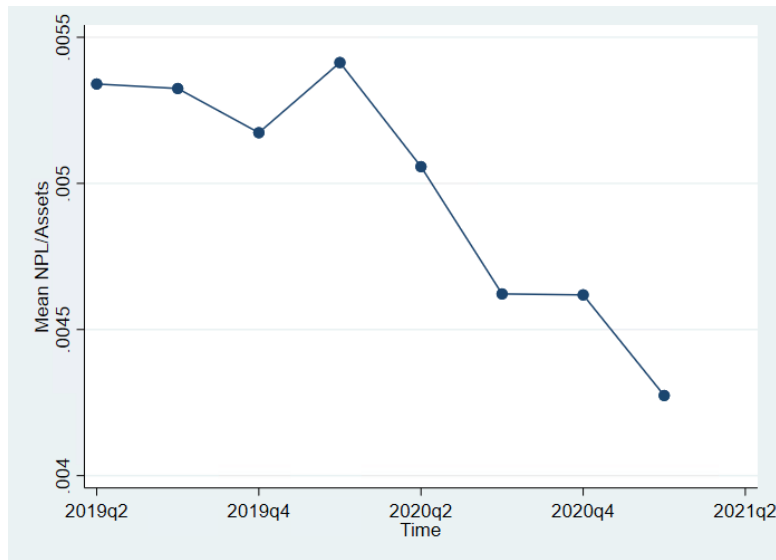


Table 1.2 shows non-performing loans disaggregated by type with commercial and industrial (C&I) loans, farmland construction, and non-farmland non-residential loans comprising the largest share of NPLs. This is not surprising as these are the loans that are most sensitive to business cycles and evidence shows that when bank’s credit standards and terms tighten, such as higher loan rates and collateralization, C&I loan balances contract (Castro et al., 2022; Lown & Morgan, 2006).

Table 1.2: NPL Types for All Bank Quarters from 2019Q1 - 2021Q1

Variables	Mean	Std. Dev.	Min	Max	N
NPL C&I loans/Assets	0.0008	0.00259	0	0.12090	40,291
All other NPL loans/Assets	0.00046	0.002706	0	0.11164	40,291
NPL depository institutions/Assets	0.00015	0.000014	0	0.00168	40,291
NPL residential construction/Assets	0.000051	0.000500	0	0.02603	40,888
Other NPL residential construction/Assets	0.00018	0.001155	0	0.04538	40,888
NPL farmland construction/Assets	0.00063	0.003272	0	0.13095	40,888
NPL owner-occupied nonfarm non-residential/ Assets	0.00072	0.002039	0	0.03947	40,888
NPL other nonfarm non-residential/ Assets	0.00050	0.001850	0	0.05929	40,888
NPL credit card	0.00055	0.000167	0	0.02071	40,291

Figure 1.4: Quarterly Mean NPL/Assets



Our dependent variable is nonperforming loans (NPL) as a ratio of total assets by bank and by quarter.¹¹ As seen in Figure 1.4, on average, banks experienced an increase in non-performing loans relative to total assets in 2020Q1, consistent with the onset of COVID-19, before declining as government and Fed pandemic economic policies are employed.

The sample is also divided into bank size categories by total asset size. Banks are categorized according to the literature by Kishan & Opiela (2000), and Jonas & King (2008), which classify community banks into four categories: those with assets below \$300 million; between \$300 and \$500 million; between \$500 and \$1 billion; and between \$1 billion and \$10 billion. We do not control for banks switching size categories due to growth, bankruptcy, mergers or acquisitions, so our panel is unbalanced. Figure 1.5 below shows that banks in every asset size category experienced an increase in non-performing loans relative to total assets between 2019Q4 and 2020Q1, the beginning of the COVID-19 period. The effect is most pronounced in the largest

¹¹ We use NPL as a ratio of total assets instead of NPL as a ratio of total loans because it captures the effect of problem loans on the overall balance sheet risk and solvency position, rather than only on the loan portfolio.

community banks category. The drop in NPL/Assets by 2020Q2 is most likely due to the PPP program starting in April 2020.

Figure 1.5: Quarterly Mean NPL/Assets by Bank Size

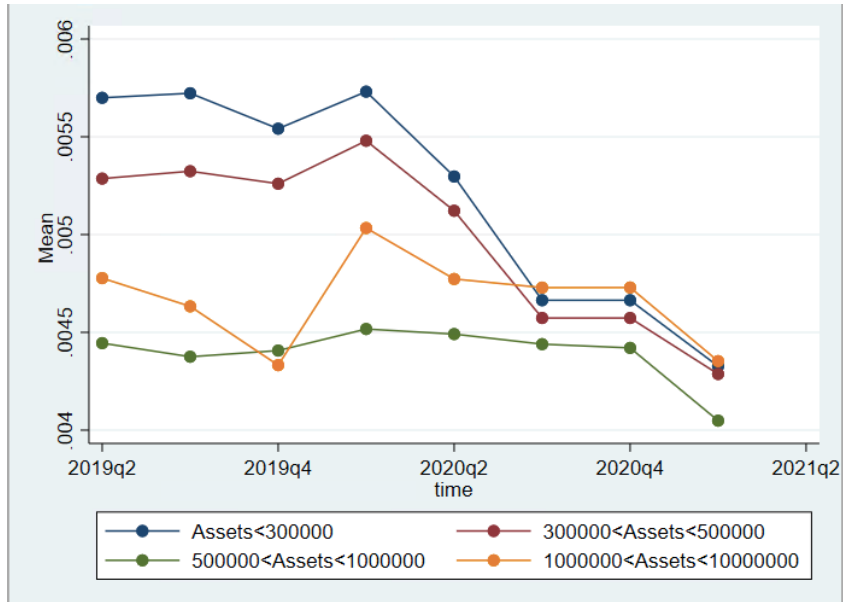
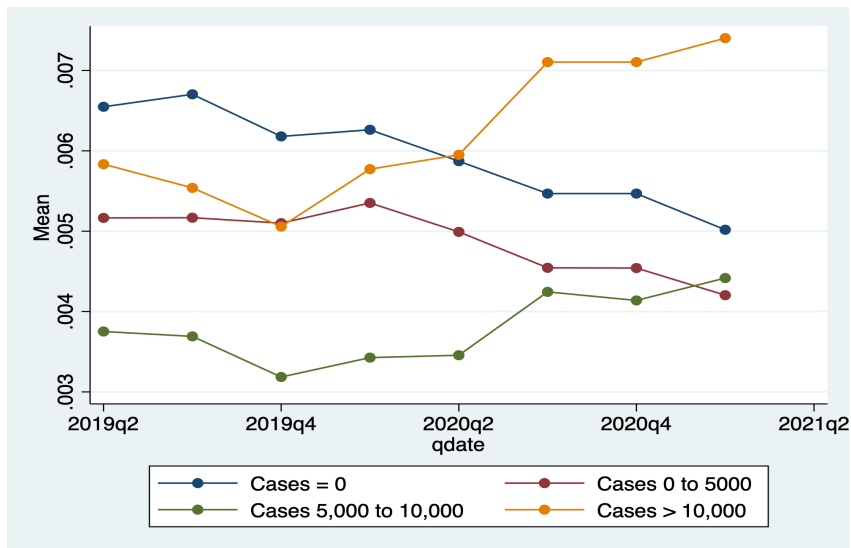


Figure 1.6 clearly shows the rise in non-performing loans for banks operating in areas most heavily exposed to COVID-19 cases (orange line). Banks operating in counties with zero levels of COVID-19 actually saw reduction in NPL (blue line).

Figure 1.6: Quarterly Mean NPL/Assets by COVID-19 Cases



According to Ari et al. (2020) in times of crisis, NPLs tend to follow a pattern of an inverse U-shape. They begin at relatively low levels, escalate quickly at the beginning of the crisis, and reach their peak some a few years later, then level off and decline. As Figure 1.6 shows, we are not seeing this exact pattern.

Figure 1.7: Mean NPL/Loans by Rural-Urban Indicator (Higher Value=more Rural)

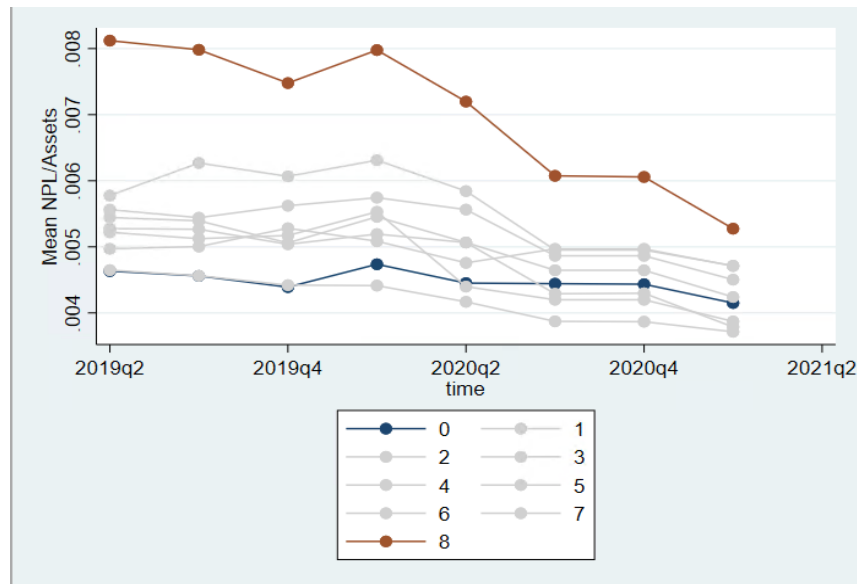


Figure 1.7 shows changes in the NPL ratio by quarter and disaggregated by the rural-urban indicator. We see two patterns. First, seven of the nine categories show increases between 2019Q4 and 2020Q2, coinciding with the onset of rising COVID cases and shelter-in-place orders (SIPOs). Second, by comparing the two extreme cases, urban (blue line) versus rural (brown line), we can see that generally, banks in rural areas have more NPLs compared to banks in urban areas and that there is a marked increase in NPLs in rural areas before a substantial decline.

1.3.3 Macroeconomic Variables

To measure monetary policy, we use two separate variables. Following Bernanke & Blinder (1992), our first measure to control monetary policy is the federal funds rate (FFR) which functions as a traditional proxy of US monetary policy. Our second measure is quantitative easing which is used as the level of assets held by the Federal Reserve, wherein a Federal Reserve purchase of assets from financial institutions will inject liquidity and expand the money supply (Samad, 2018). The reason to use this alternative method is that expansionary policy in reaction to the COVID-19 pandemic drove the Federal funds rate to the effective lower-bound which made the unconventional approach of quantitative easing necessary to increase the supply of money and facilitate liquidity and lending. For our convenience we have not accounted for the Fed's forward guidance policy which is a communication tool designed to guide expectations on future economic activity and the likely future course of monetary policy. The reason behind is that high frequency data is used to capture the changes in expectations to Fed announcements. Most of the changes in expectations following a Fed FOMC, using fed funds futures or OIS rates, can be captured within a 30-minute window (Swanson, 2021), but the quarterly nature of our data will obscure these high frequency changes in the data. Nevertheless, it is unlikely that forward guidance affects the ability to repay current loans for current debtors.

We also include the dollar value of the Paycheck Protection Plan (PPP) stimulus lending by state, and it is expected that this will reduce bank-level non-performing loans for community banks.¹² Our data also contains the US unemployment rate as an economy-wide time-series cyclical indicator.

¹² <https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program>

1.4 Empirical Model and Strategy

Our dependent variable is nonperforming loans divided by assets for bank i , in quarter t over the period 2019Q1 to 2021Q1. Our base specification includes our treatment variable of COVID-19 cases in county j (the weighted measure based on bank branch locations), as well as the treatment interacted with a monetary policy indicator (federal funds rate or Fed asset holdings). We have not included a lagged dependent variable as our time series is short Baltagi (2005) but, we do include policy indicator as first difference, macroeconomic cyclical indicators, county level controls, state fixed effect dummy variables (Ghosh, 2015), and two bank-level condition indicators as ratios relative to total bank assets (equity and total deposits).

$$Npl_{i,t} = \alpha + \beta.lnCovid_{i,t} + \vartheta.rural_{i,j,t} + \gamma.\Delta ffr_t + v.\Delta fedassets_t + \eta.X_{i,t-1} + \theta.County_{i,j,t} + \phi.Cyclical_t + \kappa.state_t + u_{i,t} \quad (1)$$

$$Npl_{i,t} = \alpha + \beta.lnCovid_{i,t} + \vartheta.rural_{i,j,t} + \gamma.lnCovid_{i,t} * rural_{i,j,t} + v_1.lnCovid_{i,t} * \Delta ffr_t + v_2.lnCovid_{i,t} * \Delta fedassets_t + \lambda.stim_{i,t} + \eta.X_{i,t-1} + \theta.County_{i,j,t} + \phi.Cyclical_t + \kappa.state_t + u_{i,t} \quad (2)$$

- $Npl_{i,t}$ = Non-Performing Loans/Assets for bank i at time t , in county j .
- $lnCovid_{i,t}$ = Logarithm of COVID cases per capita in county j , which contains bank i , at time t .
- $rural_{i,j,t}$ = County-level demographic indicator.
- $\Delta ffr_t = ffr_t$ is the effective federal funds rate at time t
- $\Delta fedassets_t = fedassets_t$ is the asset holdings of the Federal Reserve at time t .
- $stim_{i,t}$ = PPP lending by state in which bank i is located.
- $X_{i,t-1}$ = Lagged bank level controls including equity and deposits as ratios to total assets
- $county_{i,j,t}$ = Population density and population

- $cyclical_t = \text{National unemployment rate}$
- $state_t = \text{State fixed effects are binary indicators for state in which bank is headquartered, accounts for differences in pandemic response policy and economic factors.}$

The estimation strategy employed for our analysis is the Hausman-Taylor panel regression model. This approach was chosen to selectively account for potential bank-level heterogeneity bias (covariation between explanatory variables and the time-invariant bank-specific error), while allowing for state-level time-invariant fixed effects and the efficiency of a random effects transformation for higher-level geographical variables (county, state, economy-wide) that are unlikely to be correlated with bank-level effects since they are exogenous to the bank. All bank-level income and balance sheet variables were treated as endogenous with respect to the time-invariant error and instrumented using the time-demeaned version of the same variable. All other variables are treated with a random effects “quasi-demeaned” transformation. The standard errors are clustered at the bank level.

In equation (1) we have one primary coefficient of interest: the coefficient of $lnCovid_{i,j,t}$ which will be the direct effect of localized COVID-19 cases on non-performing loans. However, equation (2) includes the policy interaction effects $lnCovid_{i,j,t} * policy_t$ which will reflect how the effectiveness of expansionary monetary policy through falling ffr_t and rising $fedassets_t$ helped in mitigating the rise in NPLs during the COVID-19 pandemic.

1.5 Results and Discussion

1.5.1 Base Specification by Bank Size

Tables 1.3 show our estimation of Equation (1), which has a focus on the direct effect of COVID-19 as well as monetary policy on total non-performing loans relative to assets.

Table 1.3: Hausman-Taylor Estimation: All Banks by Size

This table shows how community and non-community banks NPLs reacted to COVID-19 crisis. Dependent variable is non-performing bank loans divided by the total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Banks are divided into five asset size categories. Bank and state fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

NPL/ Total Assets					
Variable	Sample (1) Small Banks (Assets<300M)	Sample (2) Mid-Size Banks (300M<Assets< 500M)	Sample (3) Mid-Size Banks (500M<Assets<1B)	Sample (4) Large Banks (1B<Assets<10B)	Sample (5) Large Banks (Assets>10B)
Log COVID per capita	-0.0000430 (-1.24)	0.0000548 (1.15)	-0.000008 (0.13)	0.000119* (2.28)	0.000047 (1.08)
Log COVID per capita*RURAL	-0.00000712 (-1.15)	-0.000020* (-2.18)	-0.000006 (-0.59)	-0.000026** (-3.02)	-0.000003 (0.18)
RURAL	0.000312*** (4.09)	0.000329** (3.01)	0.00016 (1.55)	0.000183 (1.66)	-0.000413 (1.39)
ΔFFR	-0.000339** (-2.53)	-0.000281 (-1.50)	-0.000236 (-1.23)	-0.000439 (-1.85)	-0.000165 (-0.80)
ΔLog Fed Assets	-0.00144** (-2.78)	-0.00176* (-2.45)	-0.00103 (-1.39)	-0.00190* (-1.97)	-0.000610 (-0.87)
Bank Fixed Effects	H-T	H-T	H-T	H-T	H-T
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Total Obs. banks	21534	5708	5171	5414	1041
Wald Chi-2 (p-value)	416.34 (0.000)	190.07 (0.000)	55.65 (0.6695)	81.45 (0.0412)	98.02 (0.000)

*Note: 2-sided z-score in parentheses. *significance at 10%; **significance at 5%; ***significance at 1%. Robust-standard errors are reported in the parentheses.*

Our baseline Hausman-Taylor specification results with the sample disaggregated by bank size are shown in Table 1.3. The coefficients on the log per-capita COVID-19 cases are significant at the 10% level for the large-size bank category between \$1 billion to \$10 billion. To put the

COVID-19 case coefficient magnitudes in perspective, we note that a 1% change in per capita COVID-19 cases across counties, is associated with a change in NPL/Assets equal to 2.38% relative to the mean for the large-size size category (sample 4).¹³ This effect is both statistically significant and economically meaningful.¹⁴

We also include non-community banks (assets above \$10 billion) in our sample and these banks do not show a significant reaction to COVID-19 cases which is consistent with Beck and Keil (2022). This is likely due to the more widely dispersed nature of branch locations for these banks, as well as the more diversified loan portfolio. This result is also an indication of the increasing separation between physical location of bank branches and overall lending activity (Berger & DeYoung, 2006).

We also find that the impact of COVID-19 cases on NPL shows regional differentiation based on the county-level rural indicator and its interaction with exposure to COVID-19 cases. For banks in the size categories below \$500 million, both the rural indicator and its interaction with exposure to COVID-19 cases are significant. However, larger community banks holding total assets between \$1 billion and \$10 billion also show significant and negative interaction of COVID-19 cases per capita and rural indicator. This indicates that community banks located in rural counties tend to have a higher ratio of non-performing loans to assets (see Figure 1.7) however, the marginal effect of rising COVID-19 cases on NPLs is smaller in rural areas, meaning that the effect of COVID-19 cases on NPL/Assets was less positive for banks located in more rural counties.

¹³ Calculated as [(coefficient estimate)] / (mean of NPL/Assets)

¹⁴ Robustness test with cumulative COVID-19 exposure to bank is documented in Appendix.

The coefficients on the alternative policy variable, Fed asset holdings, are significant for most of the bank size categories—the sign and significance indicate that quantitative easing measures were effective in reducing non-performing loans in general.

1.5.2 Policy Interaction Effect by Bank Size

We now focus on the direct test of the role that monetary policy played in mitigating the impact of COVID-19 on balance sheet health for community banks. The results shown previously in Table 1.3 established estimates of the first derivative of NPLs with respect to policy and COVID-19 individually, the hypothesis now in question is the degree to which expansionary monetary policy helped banks operating in high COVID-19 areas. Specifically, with respect to the federal funds rate, banks operating in high-COVID-19 counties should see a smaller benefit even though their borrowers would pay lower interest on debt, since firms in these areas will experience larger drops in revenue due to reduced economic activity and pandemic policy enforcement, $\frac{\partial^2 Npl_{ijt}}{\partial COVID_{ijt} \partial ffr_t} > 0$. In other words, higher COVID-19 caseloads reduce the slope of bank's reaction function relating NPL to the federal funds rate.

With respect to Federal Reserve asset accumulation, the increase in NPLs due to increased bank liquidity and associated risk-taking will also be mitigated in high-COVID-19 areas. As such, we hypothesize that $\frac{\partial^2 Npl_{ijt}}{\partial COVID_{ijt} \partial fedassets_t} < 0$ (Kandrac & Schlusche, 2021). We include both monetary policy measures in the regression as this is how the Fed responded during the pandemic.

Again, using the Hausman-Taylor panel estimator and disaggregating the sample by bank asset size, we have added the interaction between monetary policy and county-level COVID-19 cases, with results shown in Table 1.4. We have also focused our attention to the smaller

community bank categories here, so we further disaggregate by asset size. This allows for a more detailed inspection of the impact of monetary policy on smaller community banks' reactions to localized COVID-19 exposure, based on the hypothesis that costs of acquiring external funds and susceptibility to shocks may vary by asset class (Kashyap & Stein, 1995). In addition, this specification controls for PPP stimulus (STIM) lending at the state level.¹⁵

Table 1.4: Hausman-Taylor Estimation – Monetary Policy and COVID-19 Interactions by Bank Size

This table shows how community banks NPLs reacted to COVID-19 crisis and the role of monetary policy stimulus. Dependent variable is non-performing bank loans divided by the total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Community banks are divided into five asset size categories. Bank and state fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

Variable	NPL/Total Assets				
	Sample (1) (Assets<100 M)	Sample (2) (100M<Assets <300M)	Sample (3) (300M<Assets< 500M)	Sample (4) (500M<Assets< 1B)	Sample (5) (1B<Assets<10 B)
Log COVID per capita	0.0106* (2.17)	0.00887** (3.17)	0.00978** (2.89)	0.0032 (0.69)	0.00756 (1.69)
ΔFFR	0.000702* (2.39)	-0.0000459 (-0.24)	0.0000823 (0.34)	-0.000201 (-0.81)	0.000335 (1.30)
ΔFFR* Log COVID per Capita	-0.0000899 (-0.51)	-0.000125 (-1.32)	-0.000217 (-1.75)	-0.00011 (-0.53)	0.000008 (-0.08)
ΔLog Fed Assets	0.00195 (1.14)	0.000268 (0.26)	-0.0011 (-0.75)	-0.00175 (-0.70)	0.00243 (1.34)
ΔLog FEDASSETS* Log COVID per Capita	-0.000670* (-2.20)	-0.000568** (-3.25)	-0.000613** (-2.90)	-0.000200 (-0.69)	-0.000480 (-1.70)
Log COVID per capita *RURAL	-0.0000142 (-1.15)	-0.00000572 (-0.86)	-0.0000197* (-2.13)	-0.00000518 (-0.54)	-0.0000252** (-2.96)
RURAL	0.000259 (1.94)	0.000318*** (3.97)	0.000330** (3.01)	0.000152 (1.52)	0.000198 (1.83)
STIM	9.98e-12 (0.89)	8.35e-12 (1.35)	1.22e-11 (1.49)	1.59e-11* (2.07)	9.23e-12 (1.28)
Bank Fixed Effects	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES
Total Observations	8159	13375	5708	5171	5414
Wald Chi-2 (p-value)	105.48 (0.0003)	411.22 (0.000)	204.22 (0.000)	64.15 (0.4713)	97.46 (0.0045)

Note: 2-sided z-score in parentheses. *significance at 10%; **significance at 5%; ***significance at 1%. Robust-standard errors are reported in the parentheses.

¹⁵ The average loan size for all PPP loans was approximately \$67,647, with approximately 95% of PPP loans below \$150,000. These loans primarily small businesses. <https://www.finder.com/ppp-loan-stats>

The results of primary interest are the policy effects both on NPLs directly, and possible inter-relationships between policy and COVID-19 effects. Our specification includes the interactions between COVID-19 and fed funds rate as well as Fed asset holdings, seen in equations (3b) to (3c) below:

$$\frac{dnpl}{dCOVID} = b_1 + v_1ffr + v_2fedassets \quad (3a)$$

$$\frac{dnpl}{dfr} = \gamma_1 + v_1COVID \quad (3b)$$

$$\frac{dnpl}{dfedassets} = \delta_1 + v_2COVID \quad (3c)$$

We see that the coefficient on per capita COVID cases is still positive and significant for all banks with assets less than \$500 million. As the prevalence of COVID-19 cases increases in the counties where community banks operate, there is an increase in the ratio of non-performing loans to total assets. The per-capita COVID-19 caseload effects are not significant for the other bank size categories, indicating that either the composition of their balance sheet (types and risk-level of loans held) or stimulus programs were able to shield their borrowers from economic distress.

In the less than \$500 million size category, we see a significant interaction effect (coefficient estimate for v_2 in Equation (3a) and (3c)) from expansionary monetary policy as measured by Federal Reserve asset holdings. As the Federal Reserve purchased assets from the open market (quantitative easing), this stabilized bank balance sheets, reduced borrower distress, and reduced the corrosive impact of COVID-19 on non-performing loans. So, for the bank size category most heavily affected by COVID-19, Fed unconventional policy is having the intended effect of maintaining stability in the banking sector (Stever, 2011).

For banks with less than \$100 million in assets, we also see a positive and significant coefficient on the federal funds rate on our dependent variable. This indicates that the federal funds rate had a greater effect on NPLs, meaning that traditional expansionary policy based on lowering interest rates was effective but only for small bank size categories. A federal funds rate reduction generally improves both interest rate risk and default risk on bank balance sheets, leading to lower levels of NPLs (Angbazo, 1997). However, for all other bank size categories we do not see these policy improvements on risk which indicates that firms experienced significantly higher default risk (Welburn & Strong, 2020), most likely as a result of increased uncertainty and debt overextension as firms draw on credit lines as rates drop.

Again, focusing on the \$300 to \$500 million size category, Table 1.4 also shows the differential effect of COVID-19 on NPLs for banks operating in rural versus urban areas. Although we see that banks in rural areas have greater levels of NPLs relative to assets, operating in rural areas mitigated the effect of COVID-19 on NPLs. This is likely due to greater use of shelter-in-place orders and associated economic disruptions in urban areas compared to rural areas in which shelter-in-place orders were implemented later and were shorter in duration.¹⁶

Overall, the results indicate NPLs sensitivity to the COVID-19 shock among banks in the smallest size categories with assets less than \$500 million, that borrowers who transacted with these banks were less likely to benefit from government fiscal policy enacted to minimize the impact of COVID-19 crisis on small businesses such as the Paycheck Protection Program (PPP). Bartik et al. (2020) show that PPP loans funded by the federal government and administered by community banks were highly effective at reducing business failures. These bank size categories

¹⁶See <https://www.brookings.edu/events/webinar-mitigating-the-economic-impacts-of-covid-19-in-rural-areas/> and <https://bmjopen.bmj.com/content/12/4/e055791>

were more insulated by PPP lending and our results indicate that the effect of Fed asset purchases was significant in mitigating the impact of the shock on non-performing loans.

1.5.3 Policy Interaction Effect by NPL Types

Next, we segregate our dependent variable into two main categories: (1) Commercial and industrial non-performing loans and (2) All other non-performing loans. Table 1.5 shows the impact of bank-local COVID-19 cases on non-performing Commercial and Industrial Loans (C&I Loans), with the same controls and specification as in Table 1.4. C&I loans have several important characteristics that differentiate them from other type of loans. First, by definition the borrowers are bank-dependent firms, and therefore performance will be closely tied to current economic conditions. Second, they tend to be of shorter maturity than other types (real estate and personal consumption lending). As a result, C&I lending can behave very differently from other categories of bank financing at the outset of the COVID-19 crisis. Firms sought access to liquidity, and banks provided it both by generating new loans as well as utilizing pre-existing lines of credit (Li et al., 2020).

We see a positive and significant effect for mid-size bank categories in the asset range \$100m-\$300m. We also see a significant sensitivity in the non-performing C&I loans ratio to monetary policy innovations, which was also present in overall lending defaults. The negative and significant coefficient on the interaction between the level of Federal Reserve asset holdings and COVID-19 per capita indicates that as the Fed purchased assets and therefore increased bank liquidity, non-performing C&I loans decreased. Our results provide evidence that the consequences of these actions helped sustain credit and prevent further deterioration of non-

performing loans. Our results indicate that the policy outcome helped to reduce the impact of COVID-19 crisis.

Table 1.5: Hausman-Taylor Estimation – Monetary Policy and COVID-19 Interactions by NPL Type and Bank Size

This table shows how community banks Commercial and Industrial NPLs reacted to COVID-19 crisis and the role of monetary policy stimulus. Dependent variable is Commercial and Industrial non-performing bank loans divided by the total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Community banks are divided into five asset size categories. Bank and state fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

C&I NPL/ Total Assets					
Variable	Sample (1) (Assets<100M)	Sample (2) (100M<Assets <300M)	Sample (3) (300M<Assets< 500M)	Sample (4) (500M<Assets< 1B)	Sample (5) (1B<Assets<10B)
Log COVID per capita	0.00151 (0.98)	0.00298** (3.26)	0.00144 (1.21)	0.00338 (1.05)	0.00315 (1.16)
ΔFFR	0.000177 (1.59)	0.0000695 (0.99)	-0.0000129 (-0.15)	-0.0000314 (-0.24)	0.000112 (0.72)
ΔFFR* Log COVID per Capita	0.00000113 (0.02)	-0.0000478 (-1.63)	-0.0000493 (-1.01)	-0.000158 (-0.95)	-0.0000292 (0.41)
ΔLog Fed Assets	0.000360 (0.58)	0.000140 (0.41)	-0.000779 (-1.28)	-0.00198 (-0.95)	0.00128 (1.18)
ΔLog FEDASSETS*	-0.0000936 (-0.97)	-0.000189*** (-3.31)	-0.0000876 (-1.18)	-0.000206 (-1.06)	-0.000202 (-1.18)
Log COVID per Capita	-0.000006 (-1.38)	-0.0000014 (0.69)	-0.0000016 (-0.42)	-0.0000045 (1.23)	-0.0000048 (-1.05)
RURAL	0.000117 (2.33)	0.0000233 (1.22)	0.0000486 (1.66)	-0.0000294 (-0.95)	0.0000250 (0.57)
RURAL	2.92e-13 (0.08)	-2.04e-13 (-0.10)	-9.46e-13 (-0.24)	2.00e-12 (0.74)	1.84e-12 (0.40)
STIM	YES	YES	YES	YES	YES
Bank Fixed Effects	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES
Total Obs. banks	8154	13370	5699	5147	5356
Wald Chi-2 (p-value)	105.48 (0.0003)	411.22 (0.000)	204.22 (0.000)	64.15 (0.4713)	97.46 (0.0045)

*Note: 2-sided z-score in parentheses. *significance at 10%; **significance at 5%; ***significance at 1%. Robust-standard errors are reported in the parentheses.*

Table 1.6 shows the impact of bank-local COVID-19 cases on all other non-performing loans, with the same controls and specification as in Table 1.4. Not surprisingly, since the C&I NPLs category response was counteracted by non-monetary policy actions (PPP), the remaining

component is shown to be even more sensitive to COVID-19 and monetary policy mitigation than the C&I NPLs shown in Table 1.5.¹⁷

Table 1.6: Hausman-Taylor Estimation – Monetary Policy and COVID Interactions by NPL Type and Bank Size

This table shows how community banks All other NPLs reacted to COVID-19 crisis and the role of monetary policy stimulus. Dependent variable is All other non-performing bank loans divided by the total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Community banks are divided into five asset size categories. Bank and state fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

All Other NPL/Assets					
Variable	Sample (1) (Assets<100M)	Sample (2) (100M<Assets< 300M)	Sample (3) (300M<Assets< 500M)	Sample (4) (500M<Assets< 1B)	Sample (4) (1B<Assets<10B)
Log COVID per capita	0.00909* (2.07)	0.00595* (2.34)	0.00837** (2.81)	-0.000306 (-0.09)	0.00500 (1.83)
ΔFFR	0.000525* (2.00)	-0.000116 (-0.68)	0.0000986 (0.46)	-0.000212 (-1.04)	0.000191 (1.14)
ΔFFR* Log COVID per Capita	-0.000009 (-0.56)	-0.000079 (-0.89)	-0.000167 (-1.51)	0.0000452 (0.36)	-0.000052 (-0.55)
ΔLog Fed Assets	0.00159 (1.02)	0.000116 (0.12)	-0.000320 (-0.25)	0.0000745 (0.05)	0.000997 (0.78)
ΔLog FEDASSETS* Log COVID per Capita	-0.000577* (-2.11)	-0.000382* (-2.41)	-0.000527** (-2.84)	0.0000158 (0.07)	-0.000314 (-1.84)
Log COVID per capita *RURAL	-0.0000077 (-0.70)	-0.000007 (-1.22)	-0.000018* (-2.19)	-0.000009 (-1.20)	-0.000022** (-2.70)
RURAL	0.000145 (1.27)	0.000297*** (4.14)	0.000282** (2.74)	0.000182* (2.05)	0.000109 (0.85)
STIM	9.64e-12 (0.94)	8.57e-12 (1.52)	1.33e-11* (1.98)	1.40e-11 (1.87)	5.58e-12 (1.01)
Bank Fixed Effects	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES
Total Obs. banks	8154	13370	5699	5147	5356
Wald Chi-2 (p-value)	105.48 (0.0003)	411.22 (0.000)	204.22 (0.000)	64.15 (0.4713)	97.46 (0.0045)

*Note: 2-sided z-score in parentheses. *significance at 10%; **significance at 5%; ***significance at 1%. Robust-standard errors are reported in the parentheses.*

¹⁷ The categories of NPL included in table 1.6 are Real Estate (single family, multi-family, non-farm residential, construction and land development, and farmland), Individual (Credit Card, Auto, other), and Farm lending.

However, main share of this category comprises of Commercial Real Estate NPLs. Therefore, our results are consistent with the findings of Filomeni (2024) that small community banks in US were more heavily invested in commercial real estate (CRE) portfolios and experienced adverse impacts owing to pandemic-induced drop in CRE prices. Notably, the COVID-19 crisis had a more severe impact on the commercial real estate sector in the US. Pertaining to this the International Monetary Fund stated in its May 2021 report on CRE trends that “the impact of a decline in CRE prices is especially true for small and community banks, which tend to have the highest CRE loan exposures” (Fendoglu, 2021).

Overall, the results indicate a lack of sensitivity of NPLs to the COVID-19 shock among the size categories of assets more than \$500M are consistent with the finding that these community banks tend to have more conservative balance sheets and focus on relationship lending (FDIC, 2020).¹⁸ The other key factor at play is that borrowers who transacted with these banks were more likely to benefit from government fiscal policy enacted to minimize the effect of COVID-19 on business such as the Paycheck Protection Program (PPP). Bartik et al. (2020) show that PPP loans funded by the federal government and administered by community banks were highly effective at reducing business failures, which our results indicate translated into a reduction in non-performing loans on banks’ balance sheets. The bank size category most effected by the COVID-19 shock, in the \$100-500M range, therefore had less conservative balance sheets and customers more insulated by PPP lending, but our results indicate that the effect of Fed asset purchases was significant in mitigating the impact of the shock on non-performing loans.

¹⁸ <https://www.fdic.gov/resources/community-banking/report/2020/2020-cbi-study-full.pdf>

1.6 Conclusion

This study investigates the impact of COVID-19 cases at the county level on community banks' NPLs and examines the effectiveness of monetary policy in reducing the adverse effects of the pandemic on bank holdings of NPLs. We address potential endogeneity with respect to bank-specific time-invariant errors using the Hausman-Taylor panel estimator. State-level government assistance and fixed effects, as well as county-level demographic and economic indicators are controlled for.

In this paper we study the impact of COVID-19 on US community banks. Our results indicate that community banks in areas with higher COVID-19 cases experienced a statistically significant increase in aggregate non-performing loans which is consistent with the findings of Beck and Keil (2022). Our results show expansionary monetary policy as measured through the Federal Reserve asset holdings lowered the impact of COVID-19 on non-performing loans for community banks with assets less than \$500 million.

When aggregate NPLs of community banks are divided into two main categories, our findings show that with the exception of the C&I NPLs category, all other NPLs are more sensitive to COVID-19 and monetary policy mitigation. Small community banks with assets less than \$500 million are more sensitive to unconventional monetary policy when these banks are more exposed to COVID-19 caseloads. These results show the effectiveness of the Federal Reserve asset purchases in mitigating the adverse effect of COVID-19 in reducing all other NPLs.

Although our paper investigates the effectiveness of monetary stimulus measures in reducing NPLs in US community banks during the pandemic, it is important to consider certain limitations and further research directions. Findings of our paper confirms a significant role of

quantitative easing by providing liquidity to stabilize community banks' loan portfolios during the economic uncertainty of the COVID-19 pandemic however, a possible limitation is that community banks serve local communities so they may encounter challenges if economic recovery is uneven or if their customer base is still at the risk of financial instability. Moreover, the quantitative easing provided a temporary relief by injecting liquidity to stabilize financial institutions by reducing NPLs, the sustained reduction of NPLs in community banks is largely tied to the overall economic environment and the continued strength of local small businesses. For future research, it would be beneficial to explore ways which US. community banks can adapt to keep their NPLs level consistently low as monetary measure such as quantitative easing phases out.

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Appendix A

Additional Results for Chapter 1

Appendix Table 1.1: Hausman-Taylor Estimation: All Community Banks by Size – Cumulative COVID-19 Exposure

This table shows how community and non-community banks NPLs reacted to COVID-19 crisis. Dependent variable is non-performing bank loans divided by the total bank assets. Log COVID per capita is the natural logarithm of 1 + the number of cumulative COVID-19 cases per 100,000 inhabitants during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Banks are divided into five asset size categories. Bank and state fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

Variable	NPL/Total Assets				
	Sample (1) Small Banks (Assets<300M)	Sample (2) Mid-Size Banks (300M<Assets< s<500M)	Sample (3) Mid-Size Banks (500M<Assets< 1B)	Sample (4) Large Banks (1B<Assets< 10B)	Sample (5) Large Banks (Assets>10B)
Log COVID	-0.0000288 (-0.86)	0.0000540 (1.24)	-0.0000290 (0.61)	0.000159** (2.84)	0.0000525 (1.40)
Log COVID *RURAL	-0.000014* (-2.07)	-0.000021* (-2.28)	-0.0000083 (-0.86)	-0.0000195* (1.61)	0.000386 (1.32)
RURAL	0.000314*** (4.18)	0.000319*** (3.08)	0.00016 (1.65)	0.000175 (1.61)	0.000386 (1.32)
ΔFFR	-0.000310* (-2.30)	-0.000264 (-1.40)	-0.000213 (-1.07)	-0.000246 (-1.27)	-0.000567 (-0.24)
ΔLog Fed Assets	-0.00131* (-2.47)	-0.00174* (-2.45)	-0.00115 (-1.73)	-0.00225* (-2.1)	-0.000524 (-0.76)
Bank Fixed Effects	H-T	H-T	H-T	H-T	H-T
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Total Obs. banks	21528	5708	5171	5414	1041
Wald Chi-2 (p-value)	416.34 (0.000)	190.07 (0.000)	55.65 (0.6695)	81.45 (0.0412)	92.11 (0.0001)

*Note: 2-sided z-score in parentheses. *significance at 10%; **significance at 5%; ***significance at 1%. Robust standard errors are reported in the parentheses.*

In our robustness regression, we confirm that the baseline results of Table 1.2 hold when we use cumulative COVID-19 exposure using same control variables¹⁹. Significance level of our coefficient of interest is higher in the regression based on cumulative COVID-19 exposure.

¹⁹ Cumulative COVID-19 exposure is calculated as logarithm of 1 + the number of COVID cases per 100,000 inhabitants.

Appendix Table 1.2: Hausman-Taylor Estimation – Monetary Policy and COVID-19 Interactions by All Community Bank Size – Cumulative COVID-19 Exposure

This table shows how community banks NPLs reacted to COVID-19 crisis and the role of monetary policy stimulus. Dependent variable is non-performing bank loans divided by the total bank assets. Log COVID per capita is the natural logarithm of 1 + the number of cumulative COVID-19 cases per 100,000 inhabitants during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Community banks are divided into five asset size categories. Bank and state fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

NPL/Total Assets					
Variable	Sample (1) (Assets<100M)	Sample (2) (100M<Assets< 300M)	Sample (3) (300M<Assets< 500M)	Sample (4) (500M<Assets< 1B)	Sample (5) (1B<Assets <10B)
Log COVID	0.00825 (1.68)	0.00818** (3.19)	0.00705* (2.55)	0.00131 (0.45)	0.00847 (1.86)
ΔFFR	0.000628* (2.13)	-0.000269 (-1.37)	-0.0000520 (-0.22)	-0.000384 (-1.64)	0.000064 (0.21)
ΔFFR* Log COVID	-0.000049 (-0.33)	-0.000189* (-2.24)	-0.000180* (-2.01)	-0.000108 (-1.02)	-0.000237* (-2.46)
ΔLog Fed Assets	0.00227 (1.51)	-0.00124 (-1.23)	-0.00147 (-1.06)	-0.00299 (-1.67)	0.00214 (1.10)
ΔLog FEDASSETS*	-0.000524 (-1.70)	-0.000519** (-3.23)	-0.000441* (-2.53)	-0.000077 (-0.42)	-0.000522 (-1.82)
Log COVID *RURAL	-0.0000236 (-1.60)	-0.0000107 (-1.59)	-0.0000191* (-2.10)	-0.00000351 (-0.34)	-0.0000161 (-1.80)
RURAL	0.000262 (1.95)	0.000322*** (4.13)	0.000319** (3.08)	0.000150 (1.52)	0.000183 (1.68)
STIM	1.17e-11 (1.08)	8.45e-12 (1.41)	1.28e-11 (1.61)	1.52e-11* (2.21)	4.96e-12 (0.72)
Bank Fixed Effects	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Bank Control	YES	YES	YES	YES	YES
Total Obs. banks	8153	13375	5708	5171	5414
Wald Chi-2 (p-value)	105.48 (0.0003)	411.22 (0.000)	204.22 (0.000)	64.15 (0.4713)	97.46 (0.0045)

*Note: 2-sided z-score in parentheses. *significance at 10%; **significance at 5%; ***significance at 1%. Robust standard errors are reported in the parentheses.*

Table 1.2 reports robustness results for analyzing the cumulative effect of COVID-19 on NPLs by focusing on the direct test of the role that monetary policy played in mitigating the impact of COVID-19 on balance sheet health for community banks. We confirm that the results of Table 1.4 hold when we use cumulative COVID-19 exposure using same control variables to estimate

the degree to which expansionary monetary policy helped banks with high COVID-19 exposure²⁰.

Our robustness check conforms the significance of our coefficients of interest.

Appendix Table 1.3: Hausman-Taylor Estimation – Monetary Policy and COVID-19 Interactions by All Community Banks and Non-Community Banks

This table shows how community banks NPLs reacted to COVID-19 crisis and the role of monetary policy stimulus. Dependent variable is non-performing bank loans divided by the total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Banks are divided into two types based on asset size. Bank and state fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

NPL/Total Assets		
Variable	Sample (1) (Assets<10B)	Sample (2) (Assets>10B)
Log COVID per capita	0.00750*** (4.13)	0.00256 (0.72)
ΔFFR	-0.000144 (1.23)	0.0000042 (-0.02)
ΔFFR* Log COVID per Capita	-0.000085 (-1.30)	-0.000043 (-0.28)
ΔLog Fed Assets	-0.000586 (0.79)	-0.0000373 (-0.02)
ΔLog FEDASSETS* Log COVID per capita	-0.000477*** (-4.22)	-0.000160 (-0.72)
Log COVID per capita*RURAL	-0.0000145*** (-3.40)	-0.00000329 (0.19)
RURAL	0.000293*** (5.25)	0.000400 (1.36)
STIM	1.15e-11** (3.06)	7.75e-12 (0.72)
Bank Fixed Effects	YES	YES
State Fixed Effects	YES	YES
Bank Control	YES	YES
Total Obs. banks	37827	1041
Wald Chi-2 (p-value)	64.15 (0.4713)	97.46 (0.0045)

*Note: 2-sided z-score in parentheses. *significance at 10%; **significance at 5%; ***significance at 1%. Robust-standard errors are reported in the parentheses.*

In Table 1.3 when we divide our sample in only two asset size categories to distinguish the impact of COVID-19 on NPLs between community (assets less than \$10 billion) and non-community banks (assets greater than \$10 billion), we clearly see that only community banks are

²⁰ Cumulative COVID-19 exposure is calculated as logarithm of 1 + the number of COVID cases per 100,000 inhabitants.

sensitive to bank level COVID-19 cases per capita as compared to non-community banks. These findings are consistent with Beck and Keil (2022).

We also find that the impact of COVID-19 cases on NPLs shows regional differentiation based on the county-level “rural” indicator and its interaction with COVID-19. For community banks both the rural indicator and its interaction with COVID-19 exposure are significant. The negative interaction indicates that for community banks the marginal effect of rising COVID-19 cases on NPLs is smaller in rural areas. This means that the effect of COVID-19 cases on NPL/Assets was less positive for banks located in more rural counties.

Our robustness check also shows that with the Federal Reserve asset purchase bank balance sheets stabilized which reduced borrower distress and lowered the impact of COVID-19 on non-performing loans. Therefore, for community banks most heavily affected by COVID-19, the Fed unconventional policy is having the intended effect of maintaining stability in the banking sector (Stever, 2007).

Appendix Table 1.4: Variable List from the Call Reports

Variable	Source	Code
Total Nonaccrual Loans	Call Reports	RCON1407
Total Assets	Call Reports	RCON2170
Total Equity Capital	Call Reports	RCON3210
Total Deposits	Call Reports	RCON2200
NPL C&I loans	Call Reports	RCON1608
NPL depository institutions	Call Reports	RCON1386
NPL residential construction	Call Reports	RCON176
Other NPL residential construction	Call Reports	RCONf177
NPL farmland construction	Call Reports	RCON3495
NPL owner-occupied nonfarm non-residential	Call Reports	RCONf182
NPL other nonfarm non-residential	Call Reports	RCONf183
NPL credit card	Call Reports	RCONb577

2. Examining the Effects of COVID-19 and Policy Responses on U.S. Commercial Bank Deposits

2.1 Introduction

The COVID-19 pandemic, unlike the 2007-2009 global financial crisis emerged as a health crisis. The pandemic created financial and economic instability which affected the world, therefore central banks around the globe stepped up to prevent the collapse that was threatening to derail the global economy. In the United States, COVID-19 began to spread in March 2020 across many regions which triggered a deep economic slump of uncertain duration at the time.²¹ People advised by the government limited their exposure to each other under the lockdown orders. Interestingly, people managed to adjust their daily work routines and quickly changed their spending behavior. Baker et al. (2020) found that COVID-19 caused significant changes in spending habits of people in the US as they substantially increased their spending by more than 40% overall between February 26 and March 10 compared to the earlier weeks in 2020. But in the second half of March 2020, a sharp decline of about 25%–30% in individual spending was observed in areas where a higher number of cases were reported as more and more people started staying home. Moreover, Dong et al. (2021) discovered that personal consumption expenditures in the US were significantly decreased by the COVID-19 crisis for the period 24 January 2020 to 10 June 2020. In short, with the challenge of COVID-19, households confronted drastic changes in economic and financial aspects of their lives. Although investigation on the impact of COVID-19 pandemic has extended beyond 2020, focusing on this period allows to compare with more established and widely available studies.

²¹ <https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020>.
<https://www.cnn.com/2021/07/19/its-official-the-covid-recession lasted-just-two-months-the-shortest-in-us-history.html>

The COVID-19 pandemic indeed had a multifaceted impact, affecting not just economies but also financial institutions in a significant way. Studies show that the composition of bank balance sheets faced meaningful changes during the COVID-19 pandemic. This paper focuses on the liability side of the US banks' balance sheets by using Call Reports data to investigate how banks faced a significant surge in deposits during the COVID-19 pandemic. One of the reasons supported by scholarly research is that during crisis periods, depositors believe banks to be a safe place for their savings (Gatev and Strahan, 2006). My results suggest that households treated banks as a safe-haven as a response to increases in COVID-19 cases. More specifically, banks located in counties with higher levels of COVID-19 cases per capita observed an increase in deposit inflows where economic uncertainty and increased risk aversion led depositors to prioritize liquidity and safety of their funds. My study shows that a 1 percent increase in weighted per capita COVID-19 cases is associated with a change in total deposits over lagged total assets equal to 0.225 percentage points. Using a measure of COVID-19 exposure at the bank level, my results indicate that banks in counties with elevated infection rates recorded a stronger increase in their deposits. These findings are consistent with the literature which shows that banks are seen as a safe haven during crises (see, e.g., Castro et al., 2022; Dursun-de Neef and Schandlbauer, 2020).

Under the bank as safe haven view during the COVID-19 pandemic, I segregate bank deposits into core and brokered deposits to examine whether households accumulated their funds into the banks in the face of economic uncertainty due to the COVID-19 pandemic. Core deposits work as a primary source of funding for banks which they consider stable and less risky funds, received from local customers, such as savings and checking accounts. In contrast, brokered deposits are considered risky because they offer higher interest rates to attract investors and are obtained through third parties, making them more rate-sensitive and prone to rapid withdrawal.

Consistent with Dursun-de Neef and Schandlbauer (2020), it is expected that core deposits, rather than brokered deposits, account for the increase because people tend to prioritize safety and liquidity by depositing their funds in banks as a safe place to keep cash during the pandemic rather than chasing higher yields. My results indicate that banks more exposed to pandemic faced a notable increase in their core deposits, while their brokered deposits remained unchanged which aligns with the expectations. Specifically, I observe that a 1 percentage uptick in a bank's level COVID-19 exposure is associated with a 0.28 percentage point rise in core deposits as a share of total assets.

Following the effect of COVID-19 pandemic on bank deposits it is important to analyze some other essential factors that impacted bank deposit growth. Not only expansionary monetary policy played a significant role but the response of fiscal stimulus to support households and businesses also affected the liquidity and deposit trends in the banking sectors. Moreover, the effects of pandemic across regions were varying, therefore it is interesting to investigate the regional variations in bank deposits growth. In addition, bank capitalization shows a fundamental role in understanding the ability of banks to absorb and manage bank deposit inflows. Therefore, following sections will explore these key aspects by investigating how monetary and fiscal policy, regional differences, and bank capitalization impacted the dynamics of bank deposits during the pandemic.

2.1.1 COVID-19 and the Role of Monetary Policy

The monetary policy stimulus, seen during the onset of COVID-19, is considered a reason for banks to experience a surge in their deposits. The Fed actions were grounded in both conventional measures of the federal funds rate cuts as well as unconventional tools in the form of quantitative easing mainly. These actions were designed to prevent a severe economic downturn

by making credit more accessible to households and businesses. As noted by Barr et al. (2020), this influx of funds into the banking system contributed to the largest increase in bank deposits. While these actions were taken to stabilize the economy, the increase in bank deposits was unintended and a foreseeable outcome of the monetary policy stimulus. As a next step, I study whether the monetary stimulus contributed to a sustained growth in deposits with the rising local COVID cases per capita.

2.1.1.1 The Deposit Channel of Monetary Policy

The Fed used interest rate policies to regulate financial market conditions and revive the flow of funds to many sectors of the economy. These include actions to lower the fed funds rate target range by 1-1.5% and bringing it further down to 0 to 0.25% (Figure 2.1). On March 15, 2020, the Fed announced its second rate cut and reduced the rate it charged banks to borrow from its discount window from 1.75% to 0.25%. The Fed retained the fed funds rate fixed near the zero bound to ensure credit kept flowing through the financial system to households and businesses during the difficult time. This resulted as an increase in deposit inflows into the banking system. Apparently, it may seem counterintuitive that interest rate cut would result a sharp increase in bank deposit growth. Generally, lower interest rates decrease return on savings which can make depositors to reallocate their funds elsewhere for a higher return. However, the monetary policy transmission through bank deposits explains why banks experienced increase in deposits during the COVID-19 pandemic, despite this potential expectation.

The deposit channel of monetary policy works through interest rate mechanism, where fluctuations in the fed funds rate influence deposit flows into and out of banks (Drechsler et al., 2017; Drechsler et al., 2024). For example, when the Fed reduces the fed funds rate, banks narrow the spread between the market interest rate and the deposit rate they offer. Since banks have low-

interest rate beta, they exercise market power by keeping their deposit rates relatively insensitive to variations in the fed funds rate. This reduces the opportunity cost for depositors to keep their funds in the bank accounts and therefore, depositors are more likely to keep their money in checking and savings account safely instead of investing in other low return assets. Taken together, according to the deposit channel of monetary policy when the Fed cuts rate, it creates an environment where banks experience deposit inflows. Therefore, during the COVID-19 pandemic banks experienced significant deposit inflows, driven by the Fed’s decision to sharply lower the fed funds rate (Drechsler et al., 2024).

Figure 2.1: Quarterly Mean Federal Reserve Policy Rate

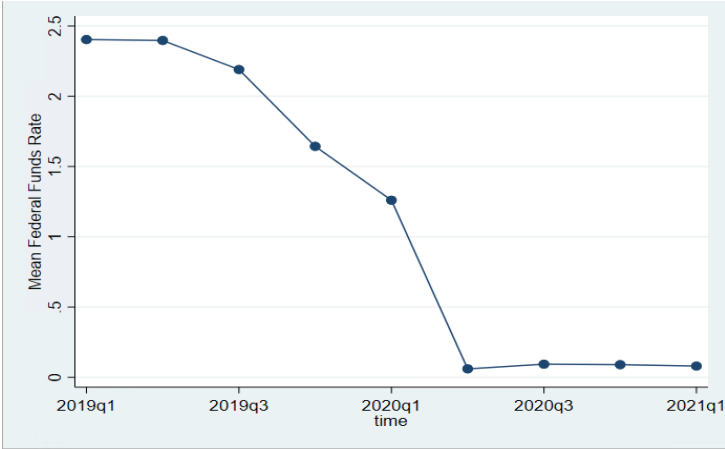


Figure 2.1 plots the average fed funds rate over time. The line depicts the fed funds rate measured in percentage at which they transacted in markets starting from 2019Q1 to 2021Q1. We can clearly see that with the onset of COVID-19 pandemic the Fed reduced the fed funds rate and kept them near the zero bound to help stabilize the economy.

Figure 2.2: Quarterly Mean Federal Funds Rate and Total Deposits of All US. Commercial Banks

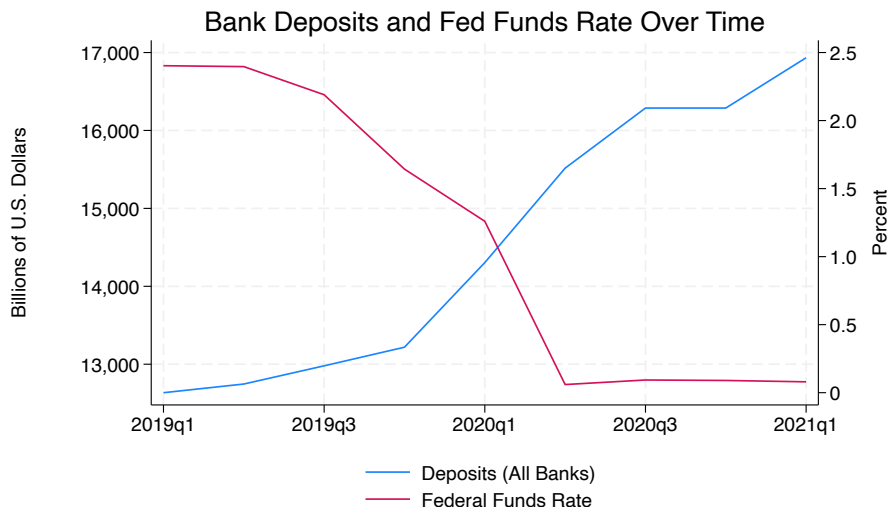


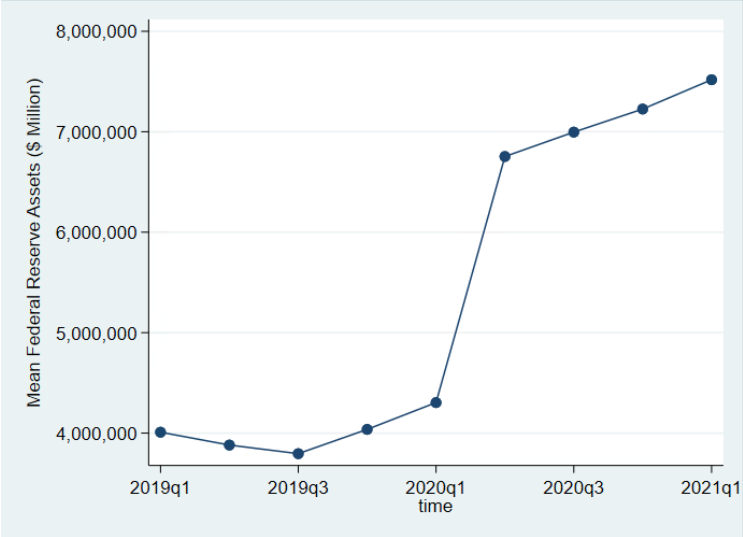
Figure 2.2 plots the total bank deposits of all US. commercial banks and the fed funds rate from 2019 Q1 to 2021 Q1. This plot zooms in on the deposit channel during the COVID-19 pandemic by showing the relationship between the fed funds rate and the total bank deposits of all US. commercial banks.

2.1.1.2 Unconventional Monetary Policy

On March 15, 2020, the Fed resumed its unconventional monetary policy tool of “quantitative easing” with the aim to increase the Treasury securities holdings to support the effective functioning of financial markets to supply credit to households and businesses. The elimination of restrictions on the Fed asset purchases led to an increase in the Federal Reserve’s balance sheet which reached an unprecedented expansion of over \$7 trillion in November 2020 (Figure 2.3). Policymakers indicated that the Fed asset purchases, and other lending programs stimulated deposit inflows to make sure that banks continued to play their essential role as credit providers (Blank et al, 2020). Figure 2.3 plots the time series of the Fed’s balance sheet expansion.

The line represents quarterly Fed’s balance sheet expansion following quantitative easing from 2019 Q1 to 2021 Q1. This helps us to visualize the Fed’s commitment to unlimited purchases of U.S. Treasuries and agency Mortgage-backed securities (MBS).

Figure 2.3: Quarterly Mean Federal Reserve Assets Purchase



Quantitative easing (QE) directly increases bank deposits by injecting liquidity into the financial system. A common misconception is the quantitative easing increases only bank reserves and affects deposits only indirectly through subsequent lending. In reality, QE directly increases deposits whenever the Federal Reserve purchases securities from nonbank entities such as households, firms, pension funds, mutual funds etc. In these transactions, the Fed credits the reserve account of the buyer’s bank, and that bank simultaneously credits the deposits account of the nonbank seller, causing an immediate rise in both reserves and deposits. Thus, QE expands the banking system’s by increasing reserves on asset side and deposits on the liability side (See Appendix Table 2.2; Appendix Figure 2.1). By contrast, when the Fed purchases securities from a bank. Reserves simply replace securities on the bank’s asset side, and no deposits are created (See Appendix Table 2.3; Appendix Figure 2.2). Because most QE operations involve nonbank sellers,

QE during COVID-19 period directly contributed to surge in bank deposits (Castro et al., 2022; Occhino, 2020).

The primary purpose of the Fed's policy in the form of reducing fed funds rate and implementing quantitative easing was to stabilize the economy by boosting lending and investment, a surge in bank deposit inflows was an anticipated byproduct. My findings also show an uptick in bank deposits because of the monetary stimulus implemented during the COVID-19 pandemic.

2.1.2 Fiscal Stimulus

Following the literature, I further expect that the large fiscal stimulus measures also contributed to a growth in deposits during the COVID-19 pandemic. Castro et al. (2022) indicate that the Paycheck Protection Program (PPP) changed the composition of the bank balance sheet by excessive deposit inflows. The PPP allowed commercial banks to issue forgivable loans for businesses to cover payroll and other operating expenses during the pandemic. Banks deposited the PPP disbursements directly into recipients' bank accounts which contributed to a large increase in deposits in the second quarter of 2020. According to Li and Strahan (2021) this effect of PPP fiscal stimulus was obvious for small community banks in processing these loans because of their strong relationship with local businesses. However, the aim of the distribution of PPP loans by these banks during the COVID-19 pandemic was to provide a transitory relief to businesses. Because these funds were quickly utilized by businesses to meet their short-term responsibilities, such as paying employees and rent, this could cause an initial spike in deposits. Research from the Federal Reserve Bank of Minneapolis also highlighted that the growth in bank deposits surged as PPP funds disbursed to businesses. But, as businesses spent these funds to meet operational needs,

the initial rise in bank deposits did not lead to sustained growth.²² Considering this perspective, my study hypothesizes whether the PPP also contributed to a sustained growth in bank deposits during the pandemic.

2.1.3 Regional Differentiation of Bank Deposits

Based on the literature, the effect of the COVID-19 pandemic on banks varied geographically. Urban areas were among the first to be exposed to the pandemic. In rural areas, the population faced an increasing burden from the pandemic, with viral transmission outpacing those of urban communities. According to Demirgüç-Kunt et al. (2020), banks were expected to play an important role to mitigate the COVID-19 shocks in the affected areas. They argued that liquidity provision, borrower relief programs, and monetary stimulus helped diminish the adverse effects of the pandemic which varied significantly across banks located in different geographical regions. Since urban banks participated in a wide range of financial activities, they were better able to take benefit from monetary and fiscal stimulus. Conversely, rural banks had less access to such resources, so they were not able to support their borrowers and maintain liquidity. Mulyati et al. (2022) find that the COVID-19 pandemic had a significant adverse impact on rural bank performance which usually work in smaller, less economically diversified regions. These banks faced challenges including rising non-performing loans due to borrowers' inability to meet repayment obligations, reduced income from lending activities, and liquidity pressures as economic activity slowed. Moreover, their weaker access to government relief programs and limited digital infrastructure worsened these challenges leading to a decline in their financial conditions as compared to their urban counterparts. Hassan et al. (2022) analyzed the comparative

²² <https://www.minneapolisfed.org/article/2021/what-did-banks-do-with-the-flood-deposits>

performance of small community and large banks in the pre-pandemic and pandemic periods and found that small community banks located in urban areas with assets less than \$10 billion significantly outperform large banks because they take advantage of strong customer relationships and better understanding of local businesses in times of economic distress. There is a growing amount of literature that examines how the pandemic impacted banks located in rural and urban areas in the U.S. However, there are no particular papers that directly compare change in deposit growth between rural and urban banks during the pandemic. The findings in my paper show that rural banks witnessed a smaller increase in deposit growth as compared to their urban counterparts because of weaker access to monetary and fiscal stimulus benefits which resulted in low income and less disposable income to save.

2.1.4 Bank Capitalization

A bank needs capital to stay safe, protect people's deposits and absorb losses to keep going in good times and bad.²³ The traditional function of bank capital is to protect bank depositors against loss. Bank capital is a first line of deposit guarantee (Robinson, 1941). Better-capitalized banks experience a more rapid increase in deposits than poorly capitalized banks (Arping, 2019). Banks with more equity become safer and the cost of deposit funding reduces which in turn induces banks to increase their deposits. Moreover, monetary policy transmission is more pronounced for well-capitalized banks (Van den Heuvel, 2005). Community banks, varying in size from below \$50 million in assets to as large as \$1 billion to \$10 billion in assets, are generally well capitalized and more conservative. They are systematically better equipped to handle both good and bad

²³ https://www.bankingsupervision.europa.eu/about/ssmexplained/html/hold_capital.en.html

times.²⁴ However, temporary capital relief measures during the COVID-19 pandemic in the U.S. were introduced to ensure that banks could continue lending and supporting economic activity without breaching regulatory capital requirements. According to Abboud et al. (2021) reducing capital buffers allows banks to use more capital to absorb losses and extend credit to businesses and households affected by the economic downturn. Taking this view into consideration, my study investigates whether small banks with higher capital experienced more deposit inflows. Following Kishan & Opiela (2000), I choose to segregate small banks into three capital leverage ratio groups: $< 8\%$ (undercapitalized), $\geq 8\%$ and $< 10\%$ (adequately capitalized), and $\geq 10\%$ (well capitalized). I classify only small banks into three capital ratio groups because small banks typically rely more heavily on deposit funding and face greater competition from larger institutions (Egan et al., 2022). My results show that small well-capitalized banks with capital leverage ratio $\geq 10\%$ and assets less than \$500 million experienced a surge in deposits during the pandemic as these banks are better equipped to handle crisis periods because they maintain a conservative outlook towards risk exposure and have closer ties to their customers.

In terms of contribution, my study is related to Dursun-de Neef & Schandlbauer (2020). They find that households increased savings in bank deposit accounts during the COVID-19 pandemic. As a result, banks operating in counties with elevated exposure to COVID-19 recorded a significant growth in their deposits. Moreover, my research is relevant and adds to the larger literature on banks as safe havens during crisis. Using the sample data of at most 46,591 bank observations from the period 2019Q1 to 2021Q1, my fixed effects panel approach examines the influence of the COVID-19 pandemic on bank deposits which differs from the study of Dursun-de

²⁴ <https://www.stlouisfed.org/news-releases/2013/05/24/st-louis-fed-study-shows-community-bank-model-can-thrive-in-good-times-and-in-bad>

Neef & Schandlbauer (2020) in a few important ways. First, it investigates the impact of potential expansionary monetary policy responses on bank deposits with a rise in COVID-19 cases per capita for all the banks located in different counties. Second, it examines the effect of fiscal stimulus as a contributor to a sustained growth in deposits during the pandemic. Third, it evaluates the relationship between COVID-19 cases per capita and bank deposits with a possibility of geographic differentiation in banks. Fourth, this paper segregates banks in different bank size categories to provide consistent marginal effects of monetary and fiscal policy on bank deposits. Lastly, this study divides banks based on their leverage ratios to investigate how banks with differing financial stability responded to monetary policy transmission to deposits amid the COVID-19 crisis.

The remainder of the paper is structured as follows: section 2 reviews the literature relating to COVID-19 effects on bank deposits; section 3 discusses the data and descriptive statistics; section 4 presents the empirical specifications for the model of bank deposit in response to COVID-19 cases and monetary and fiscal policy; section 5 presents the results of both the full bank sample and subdivided bank sample which categorize the banks with total assets below \$500 million, banks with total assets between \$500 million and \$1 billion, and banks with total assets above \$1 billion; and section 6 concludes the paper.

2.2 Literature Review

In terms of work on how the banking system has been affected during the pandemic, a few scholarly articles are relevant for this paper. The study by Dursun-de Neef & Schandlbauer (2020) uses a fixed effect model with a bank-specific COVID-19 exposure computed as the weighted average COVID-19 per capita cases where weights reflect the share of deposits the bank holds in each county where it maintains a branch. Their panel data examination explores U.S. commercial

banking activity during the period 2018Q1 to 2020Q1 using income statement and balance sheet data showing that as the severity of the COVID-19 crisis varied substantially across the US., banks with greater exposure encountered a substantial increase in their deposits. Their findings indicate that households increased their savings unintentionally because they encountered fewer opportunities to spend their funds during the COVID-19 pandemic. Baker et al. (2020) also confirm that household consumption in the US. is heavily reliant on outbreak severity in a given state, and the intensity of the local government's response. Their study shows that consumer spending decreased sharply with the onset of the pandemic. My study is relevant for the work on whether households consider banks a safe place to deposit their money when the economy faces a crisis. According to Gatev & Strahan (2006), during times of distress banks can provide lending easily to their borrowers. Banks have this unique ability of liquidity provider since they experience a higher deposit inflow as households seek banks as a safe place. In addition, Gatev et al. (2009) use data on bank characteristics based on the latest quarterly Call Reports (Reports of Income and Condition) and find that banks experience inflows of deposits when the market liquidity dries up as compared to other financial intermediaries. This provides evidence that banks are seen as safe places for money and investors tend to move funds into bank deposits amid episodes of market stress. Consistent with this, Acharya & Mora (2015) detail how banks offer higher deposit rates to attract deposit inflows to avoid increasing solvency risk during episodes of financial distress. Their main result provides evidence that in the 2007-2009 financial crisis, the lending growth rate of the banks outpaced the deposit inflows leading to a loan-to-deposit shortfall until the government intervened. This deposit shortfall is explained as an investor's perception of greater risk in bank deposits if they are not backed by the government. The fact is that during a crisis the households increase their savings in banks not because the banks offer higher deposit rates but because they

consider banks as a safe place as they are backed by the government. My work offers a contribution by showing that banks experienced a positive deposit inflow during COVID-19 pandemic as banks are seen as a safe place by households.

The COVID-19 outbreak has significantly hampered economic performance through a range of demand and supply channels. Adaptation to monetary policy, such as interest rate cuts and quantitative easing can stabilize the economy from such volatility shocks. Consistent with this, Cúrdia (2020) suggests that enabling a rapid decline in the fed funds rate will support the economy in dealing with the COVID-19 outbreak. Moreover, Drechsler et al. (2017) proposed a deposit channel of monetary policy transmission which explains how monetary policy impacts banks' funding the economy. Their findings show a strong impact of a change in the fed funds rate on the bank deposits to flow in or out of the banking system. From this perspective, Agarwal et al. (2021) suggest that expansionary monetary policy has triggered massive increases in deposits. Moreover, as the purpose of unconventional monetary policy tool like quantitative easing is to ensure the smooth functioning of financial markets to provide credit to household and businesses, Blank et al. (2020) indicates that the Fed asset purchases made sure that banks continued to play their essential role as credit providers which resulted as an increase in bank deposit growth. My paper contributes to this literature by investigating the strength of counter-cyclical monetary policy in the massive increase in deposits with the outbreak of COVID-19.

Since bank capital plays a significant role in ensuring bank stability and credibility, it acts as a financial buffer that absorbs losses and supports ability of banks to operate under adverse conditions. Peek & Rosengren (1995) explored the effects of bank capital on credit availability during economic downturns. They find well-capitalized banks are more resilient and less likely to shrink their balance sheets during capital shocks leading to an increase in depositors' confidence.

Historically, the literature also suggests that large and well-capitalized banks are likely to be backed by the government, therefore they are considered to be safer than small less capitalized banks. According to Gatev et al. (2009) and Morrison (2011) large well capitalized banks are more supported by the government as compared to small banks in times of economic distress. Therefore, the reason that banks experience deposit inflows during market turmoil is because they are considered as safe havens since the government insures them. Consistent with this, recent research conducted by Dursun-de Neef & Schandlbauer (2020) on bank deposits and COVID-19 in which their sample is based on well-capitalized banks where the average bank has \$5.8 billion in total assets. They segregate their bank balance sheet data into two asset size categories i.e., larger banks and smaller banks and find that only larger banks experience bank deposit inflows. My study instead divides the sample into three asset size categories to evaluate the influence of COVID-19 on bank deposits. Moreover, my study also investigates the effects of the pandemic on bank deposits under different potential expansionary policy responses for banks with three asset size categories. Kashyap & Stein (1995, 2000) in their study find that monetary policy operates through small banks because these banks face difficulties in increasing non-reservable liabilities opposite to large well-capitalized banks. Consistent with this study, Kishan & Opiela (2000) employed balance sheet data obtained from quarterly Call Reports from 1980Q1 to 1995Q4 for 13,042 commercial banks. By using linear Dynamic Panel Data (LDPD) model their study observed that small banks exhibit greater sensitive to monetary policy actions relative to large banks. Conversely, monetary policy operation tends to benefit well-capitalized banks more than less capitalized banks (DeYoung & Duffy, 2005). My paper contributes to the existing relevant literature by examining the sensitivity of the banks to monetary policy transmission.

2.3 Data and Descriptive Statistics

2.3.1 COVID-19 and County-Level Data

The data on COVID-19 used in this study is acquired from Johns Hopkins University's Center for Systems Science and Engineering (CSSE) which provides daily COVID-19 case counts for each U.S. county, starting on January 22, 2020.²⁵ Following Beck & Keil (2022) for COVID-19 case exposure at the bank level, I compute an indicator of “average exposure” to areas where a bank operates branches, using 2019 branch-level deposit shares in total bank deposits as weights for each county.²⁶ Thus, the treatment variable is the logarithm of the bank-level exposure to COVID-19 related cases where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 inhabitants during a quarter in a US. county.²⁷ Additionally, my data contains quarterly county-level demographic control variables. These include population, population density and a rural-urban indicator and the data is collected from US Census Bureau and USDA (US Department of Agriculture).²⁸

2.3.2 Bank Data

Bank data are taken from the quarterly Call Reports filed by all FDIC-insured commercial banks with the Federal Financial Institutions Examinations Council (FFIEC), which is commonly

²⁵ Number of confirmed COVID-19 cases for each US. county starts on January 22, 2020.

JHU has stopped collecting COVID data since 03/10/2023; <https://coronavirus.jhu.edu/map.html>

²⁶ Based on Federal Deposit Insurance Corporation's Summary of Deposits data

²⁷ In order to handle zero COVID cases, COVID-19 exposure is calculated as logarithm of 1 + the bank level exposure to COVID cases.

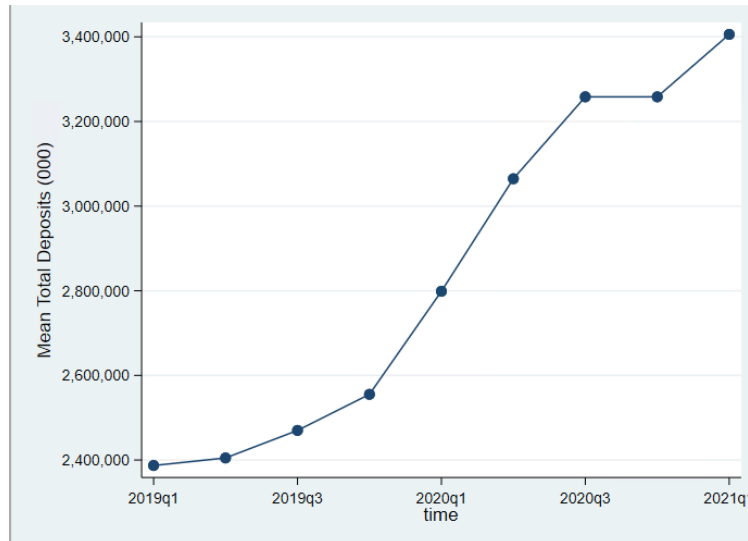
²⁸ The rural - urban indicator ranges from 0 to 8, a higher value indicating that the county is more rural. Control variables like population, population density and rural-urban indicator account for regional differences that can influence growth in bank deposits. County population indicates the total no. of people living in the county. Population density is measured as the no. of people per square mile.

<https://www.census.gov/data/datasets.html>

<https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data/>

used in this literature. The quarterly data set of the cross-sectional bank balance-sheet forms an unbalanced panel data from the period 2019Q1 to 2021Q1. The variable list can be found in the appendix, and full descriptive statistics can be found in Table 2.1. In total, the sample comprises 46,591 bank observations with the number of banks equal to 5177.

Figure 2.4: Average Deposits by Quarter



As seen in Figure 2.4, on average, banks experienced a persistent increase in total deposits since 2020Q1, consistent with the onset of COVID-19. The graph clearly displays liability side of the commercial bank balance sheet composition which changed during the pandemic as banks faced a surge in their total deposits.

The sample is also divided by total asset size categories. Size category is based on the literature by Kishan & Opiela (2000) and Jonas & King (2008) which categorizes banks into three groups: those with total assets below \$500 million, between \$500 million and \$1 billion, and above \$1 billion. It is worth noting, I do not control for banks switching size categories due to growth, bankruptcy, mergers, or acquisitions and so the panel is unbalanced.

2.3.3 Cyclical and Policy Variables

Monetary policy is included by using two separate variables. First, the fed funds rate, long held as the standard indicator of US. monetary policy stance (Bernanke & Blinder, 1992). As discussed earlier, expansionary policy in reaction to the COVID-19 pandemic pushed the fed funds rate to the effective lower-bound, requiring the use of an alternative method of monetary policy, specifically quantitative easing, to expand the supply of money and facilitate liquidity. The second measure, quantitative easing, is the level of assets held by the Fed, wherein a Fed purchase of assets from financial institutions will inject liquidity and expand the money supply (Samad, 2018). I note that I have not controlled for the Fed's forward guidance policy. The Fed's forward guidance policy is a communication tool designed to guide expectations on future economic activity and the likely future course of monetary policy. Typically, high frequency data is used to capture the changes in expectations to the Fed announcements. Most of the changes in expectations following a Fed FOMC, using fed funds futures or OIS rates, can be captured within a 30-minute window (Swanson, 2021), but the quarterly nature of my data will obscure these high frequency changes in the data.

I also include the dollar value of the Paycheck Protection Plan (PPP) stimulus lending by state.²⁹ My data also contains the national unemployment rate as an economy-wide time-series cyclical indicator.

Table 2.1 presents summary statistics for the key variables used in the analysis. In total, the sample contains at most 46,591 bank observations (based on 5177 banks over 9 quarters). Table

²⁹ <https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program>
In order to handle zero value of PPP, PPP fiscal stimulus is calculated as logarithm of 1 + the dollar value of the Paycheck Protection Plan (PPP) stimulus lending by state.

2.1 shows the mean balance sheet ratios for all bank quarters from 2019Q1 to 2021Q1. The variable list from the Call Reports can be found in the appendix. Banks in my sample hold an average of almost \$3.7 billion in total assets. This means that banks maintain adequate capitalization and are financially stable. The mean ratio of total equity to total assets is 12% which is generally considered as a healthy and well-capitalized position while the average bank reports a return on assets which is the net income is 0.7% and interest income of 2.6%. On average, banks hold 9.2% of their assets in cash. Banks finance 83% of their assets mainly by deposits.

Table 2.1: Summary Statistics for all Banks from 2019Q1 – 2021Q1

Variables	Mean	Std. Dev.	Min	Max	N
Bank-Level Data					
Assets (000)	3,798,138	58,800,000	3408	3,210,000,000	46,150
Total Deposits (000)	2,835,636	40,400,000	24	1,990,000,000	46,165
Deposits/Assets	0.830	0.093	0.0003	0.983	46,150
Δ Deposits/lagged Assets	0.034	0.458	-0.727	89.861	40,775
Δ Core Deposits/lagged Assets	0.041	0.098	-1.189	4.848	35,552
Δ Brokered Deposits/lagged Assets	-0.0001	0.005	-0.243	0.320	35,552
Equity/Assets	0.123	0.069	0.003	0.992	46,060
Non-performing Loans/Assets	0.005	0.008	0	0.188	40,841
Net Income/Assets	0.007	0.039	-0.271	3.978	40,864
Cash/Assets	0.092	0.100	0	0.998	46,133
Interest Income/Assets	0.026	0.014	0	0.249	40,864
County-Level Data					
COVID cases	10,589.06	53,597.39	0	1,219,614	45,632
Log (COVID cases)	3.892	4.144	0	14.014	45,632
Log (COVID cases per capita) (weighted)	3.817	3.914	0	10.855	45,652
Population	455,703.5	1,207,894	431	10,000,000	46,399
Population Density	525.741	1794.597	0	17995.9	46,106
Rural-Urban Indicator	2.895	2.616	0	8	45,033
Macro-Level Data					
Fed Funds Rate	1.157	1.003	0.06	2.403	46,165
Log (Fed Assets Purchase)	15.452	0.288	15.149	15.833	46,165
Fiscal Stimulus	2,090,415	5,679,668	0	43,500,000	46,590
Unemployment Rate	5.877	3.058	3.533	13.033	46,115

2.4 Empirical Model

The initial goal of this research is to examine the effect of the COVID-19 pandemic on total bank deposits. Following Dursun-de Neef and Schandlbauer (2020) my baseline empirical model is.

$$\begin{aligned} \Delta Total\ Deposits/Total\ Assets_{i,t-1} \\ = \alpha + \beta. lnCovid_{i,t} + \vartheta. rural_{i,j,t} + \gamma. \Delta ffr_t + \nu. \Delta fedassets_t + \lambda. stim_{i,t} \\ + \eta. X_{i,t-1} + \theta. County_{i,j,t} + \phi. Cyclical_t + \kappa. state_t + \delta_i + \delta_t + \varepsilon_{i,t} \end{aligned} \quad (1)$$

where i, j and t index bank, county and time period. In my model the dependent variable is the first difference in total bank deposits divided by the lagged total bank assets for bank i at time t. The primary coefficient is β which represents COVID-19 cases per capita in county j, which contains bank i, at time t. $X_{i,t-1}$ is a matrix of control variables which includes the size of the bank measured as the logarithm of total assets as well as a set of other bank characteristics which are considered components of a bank's characteristics according to Lopez (1999). These bank characteristics included total equity which is chosen as a proxy for bank's capital adequacy, loan loss reserves proxy for bank's asset quality, net interest income proxy for management quality, return on assets proxy for earnings, cash proxy for liquidity. This set of bank characteristics is added in regression as the lagged bank-level ratios.³⁰

Dependent variable is further segregated into two main categories. Core deposits, measured as the first difference in total core deposits divided by the lagged total bank assets for

³⁰ In the matrix of control variables, each bank characteristic variable is divided by total assets and then lagged one period.

bank i at time t .³¹ Brokered deposits are measured as the first difference in total brokered deposits divided by the lagged total bank assets for bank i at time t .

To additionally control for unobserved heterogeneity, bank fixed effects δ_i and quarter-year fixed effects δ_t are included. Moreover, state-fixed effects interactions with a time varying variable (national level unemployment rate) are added in the regression which accounts for differences in pandemic response policy and economic factors for banks headquarter in that state. The ε_{ijt} term is the time-varying idiosyncratic error.

To estimate the relationship between conventional monetary policy and total bank deposits, this study tries to investigate how the change in bank deposits respond to a decrease in fed funds rate with the rise in COVID-19 cases per capita. The degree of change in total deposits in response to policy is measured by the coefficients on the first difference in the fed funds rate Δffr (Jonas & King, 2008; Kashyap & Stein, 1995; Kishan & Opiela, 2000). The difference operator is used to calculate the change in fed funds rate across periods.

Equation (2) below exhibits the marginal effect of conventional monetary policy on the change in bank deposits which shows the expected coefficient associated with the first difference of the policy indicator to be negative. Specifically:

$$\frac{\partial(\Delta Total\ Deposits/Total\ Assets_{ijt-1})}{\partial(\Delta ffr_t)} = \gamma \quad (2)$$

³¹ Measured as Interest bearing demand deposits plus non-interest-bearing demand deposit plus Money Market Deposit Accounts (MMDAs) plus Other Savings Deposits plus Time Deposits less than \$250,000 (Vatsa, 2021).

Further, equation (3) details the marginal effect of the fed funds rate on bank deposits with an interaction with the log COVID-19 cases per capita. The effect is expected to be more negative when the fed funds rate is reduced following an expansionary policy during pandemic.

$$\frac{\partial(\Delta Total Deposits/Total Assets_{i,j,t-1})}{\partial(\Delta ffr_t)} = \gamma + \lambda \cdot COVID_{it} \quad (3)$$

For the unconventional monetary policy namely quantitative easing, the Fed's asset purchases are used as the policy variable. Following the literature, the coefficient on the log of first difference in the Fed's asset purchase $\Delta fedassets$ is used to measure the degree of change in total deposits in response to unconventional monetary policy when the fed funds rate is near zero lower bound.

Equation (4) describes the marginal effect of unconventional monetary policy on the change in bank deposits as the coefficient associated with the log of differenced Federal Reserve asset accumulation is assumed to be positive.

$$\frac{\partial(\Delta Total Deposits/Total Assets_{ijt-1})}{\partial(\Delta Fedassets_t)} = \nu \quad (4)$$

Further, equation (5) shows the marginal effect of the Federal Reserve's asset accumulation on bank deposits with an interaction with the log COVID-19 cases per capita. The effect is expected to be positive and becoming more so with the increase in Fed's asset accumulation during the pandemic.

$$\frac{\partial(\Delta Total Deposits/Total Assets_{ijt-1})}{\partial(\Delta Fedassets_t)} = \nu + \lambda \cdot COVID_{it} \quad (5)$$

The identification strategy rests on the assumption that the key regressors - bank-level COVID-19 exposure and national monetary policy actions are plausibly exogenous within the empirical framework. COVID-19 exposure is constructed using pre-pandemic deposit shares to

weight county-level cases, making the measure external to bank's deposit behaviour, as the geographic evolution of the pandemic is unrelated to individual bank decisions. Bank fixed effects remove all time-invariant differences across banks, while time fixed effects absorb national shocks, so the remaining within-bank variation in COVID-19 exposure can be treated as as-good-as random for identification purpose. Monetary policy variables are shocks that no individual bank can influence so it is exogenous at the bank level. Identification therefore arises from heterogeneous responses across banks, driven by differences in COVID-19 exposure.

If the exogeneity assumptions are violated, the direction of bias is predictable. For COVID-19 exposure, bias can arise if COVID cases are correlated with unobserved county-level shocks such as lockdown measures, that also affect deposit growth. For instance, the estimated COVID-19 coefficient can be biased upward if higher COVID cases coincided with stronger household savings or biased downwards if severe COVID-19 outbreak is associated with economic contraction that reduces deposit inflows. For monetary policy, bias can occur if policy actions occur in response to periods of financial stress when deposits are already declining, then the estimated effects may be biased toward zero or negative implying that the true expansionary impact of monetary policy on bank deposits is likely larger than what the estimates suggest.

2.5 Main Results and Discussion

2.5.1 Base Specification

I divide this section into two parts. The first shows the baseline results of the impact of COVID-19 on my entire sample of bank deposits. The second section examines whether the effect of monetary policy on bank assets is conditional in nature by interacting COVID-19 with the fed funds rate and the Fed asset purchases.

The first goal is to show the impact of the initial COVID-19 outbreak on banks' deposit holdings across all banks. Table 2.2 displays three specifications of fixed effects regressions testing the impact of COVID-19 on total bank deposits. Column 1 includes the main explanatory variable (the logarithm of 1 + the bank level exposure to COVID-19 related cases per capita), cyclical and policy variables, controls such as the lagged bank level ratios, bank size and county controls such as population, population density and a rural-urban indicator without its interaction with COVID-19 related cases per capita.

To put the COVID-case coefficient magnitudes in perspective, I note that a 1 percent increase in per capita COVID cases across counties, is associated with a change in Δ Total Deposits/lagged Assets equal to 0.108 percentage points. This effect is both statistically significant and economically meaningful. This result is consistent with the findings of Dursun-de Neef & Schandlbauer (2020, 2022). This is likely due to banks' “safe haven” view when banks are considered safer for households to accumulate savings in their bank accounts. Moreover, the positive and significant coefficient on the national unemployment rate supports the findings by Mody et al. (2012) which observes that changes in the unemployment rate – a proxy for variation in economic uncertainty raised precautionary savings levels which led to increase in bank deposits during the pandemic.³²

³² <https://internationalbanker.com/banking/why-bank-deposits-are-at-record-levels/>

Table 2.2: Impact of COVID-19 on Bank Deposits

This table shows how bank deposits reacted to COVID-19 crisis. Dependent variable is the first difference in total bank deposits divided by the lagged total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Bank and quarter-year fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

Variable	Δ Total Deposits/Total Assets _{i, t-1}		
	(1)	(2)	(3)
Ln (COVID per capita)	0.00108* (2.05)	0.00225*** (3.74)	0.00225*** (3.75)
RURAL	-0.000954 (-0.43)	0.000129 (0.02)	0.000143 (0.03)
Ln (COVID per capita) *RURAL	-	-0.000176*** (-5.01)	-0.000176*** (-5.02)
Δ FFR	-3.306*** (-16.01)	-3.341*** (-28.03)	-3.183*** (-6.43)
Δ ln (Fed Assets)	9.358*** (28.46)	9.371*** (39.08)	8.962*** (7.10)
Cash/Assets	-0.133*** (-7.16)	-0.133*** (-14.95)	-0.133*** (-14.95)
Equity/Assets	0.167 (1.22)	0.166*** (6.32)	0.166*** (6.32)
Nonaccrual loans / assets	-0.101 (-1.11)	-0.121 (-1.20)	-0.121 (-1.20)
Net Income / assets	0.0888* (2.04)	0.0891*** (4.05)	0.0890*** (4.05)
Interest income / assets	-0.208 (-0.72)	-0.206* (-2.07)	-0.206* (-2.07)
Ln (assets)	-0.255*** (-9.93)	-0.257*** (-51.20)	-0.257*** (-51.20)
Ln (Population)	-0.00511 (-0.75)	-0.00715 (-1.10)	-0.00718 (-1.10)
Population density	-0.00000854** (-2.70)	-0.00000846*** (-4.24)	-0.00000846*** (-4.24)
Unemployment rate	0.0621*** (10.65)	0.0629*** (22.28)	0.0606*** (8.08)
Ln (Stimulus)	-	-	-0.000173 (-0.33)
Total Obs. Banks	34046	34046	34046

*Note: The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

However, when I added an interaction term of a rural-urban indicator with COVID-19 related cases per capita in column 2 and 3, the results show a more significant and meaningful result about the impact of COVID-19 cases on bank deposits which is 0.225 percentage points.

The impact of COVID-19 cases on bank deposits also shows regional differentiation. The significant coefficient of county-level rural indicator with its interaction with $\ln(\text{COVID-19 per capita})$ indicates that rural banks tend to have a smaller increase in their deposits to assets ratio with the rising COVID-19 cases as compared to banks located in urban areas. This is possibly because of the disruption caused by pandemic leading to massive job losses in rural areas and fewer funds to save. These results are aligned with the findings of Sano & Mammen (2022). They analyzed economic and social data specific to rural populations to examine the significant challenges that rural low-income families faced during the COVID-19 pandemic. These results indicate that rural areas experienced increase in deposit inflows due to government stimulus payments, but these gains were smaller than in urban areas because rural economies, reliant on industries heavily impacted by the pandemic, had less disposable income to save and faced challenges like limited digital banking access.

Table 2.2 also controls for expansionary monetary policy in all columns. To interpret the result, for example, in column 2, the coefficient on the first difference value of the fed funds rate is significant which indicates the effectiveness of monetary policy leading to increased bank deposits. As the fed funds rate is reduced by 1 percentage point bank deposits increase by 3.341 percentage points. These findings indicate that when the fed funds rate decreases, it primarily affects the supply of deposits. Banks decrease deposit spreads and increase total amount of deposits, showing that they were more likely supply deposits at lower rates.

Moreover, the positive and significant coefficient on the Fed asset purchases indicates a 1 percent increase in the Fed's asset purchase is associated with a 9.324 percentage points increase in bank deposits which suggests contribution of the Fed's asset purchase to a spike in bank deposits

by injecting large amount of liquidity into the financial system.³³ When the Fed purchases assets, it pays the non-bank financial institutions by crediting their bank accounts. This process increases the reserves that banks hold, which then get reflected as higher deposits in the accounts of individuals and institutions. As the Fed injects liquidity through asset purchases, these funds flow into banks, expanding their deposit base. These findings are consistent with Emmons (2022) who shows that the large-scale asset purchases by the Fed during COVID-19 led to an increase in core deposits of similar magnitude.

I further view that banks with higher levels of equity tend to have more assets than liabilities and therefore they can attract more customers and have more deposits. The negative and significant coefficient on cash indicates an increase in cash holdings of banks reduces bank deposits. If banks increase their cash holdings to manage liquidity, then there will be a contraction in loan supply of the banks which may result as a fall in bank deposits. This is consistent with Cornett et al. (2011) who claims that banks first increase their cash holdings to manage the liquidity shocks during crisis times before they supply loans and increase their deposits. Finally, Table 2.2, column 3 controls for fiscal stimulus (PPP lending). The lack of a significant relationship between growth in deposits and PPP fiscal stimulus reveals the temporary nature of immediate liquidity insertions caused a brief increase in bank deposits. This conclusion is in line with Levine et al. (2021), that the impact of COVID-19 uncertainty on the growth of bank deposit was more lasting compared to the short-lived effect of PPP.

Next, I segregate bank deposits into core and brokered deposits which is crucial to investigate bank as safe haven view during the pandemic. Since “safe haven” view emphasizes

³³ The Fed asset accumulation is measured as log of first difference; therefore, to simplify the results 1 percentage increase in Fed asset purchase is associated with an increase of $9.371 * \log(1.01) \approx 0.09324$ in deposits which is $0.09324 * 100 = 9.324$ percentage points.

that during crises, like the pandemic, individuals and institutions view banks as a secure place to store their money, leading to an influx of deposits.

Table 2.3: Impact of COVID-19 on Core and Brokered Deposits

This table shows how two types of bank deposits reacted to COVID-19 crisis. Dependent variable is divided into two categories core and brokered deposits. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Bank and quarter-year fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

Variable	Δ Total Deposits/Total Assets _{i, t-1}	
	Δ Core Deposits/Total Assets _{i, t-1}	Δ Brokered Deposits/Total Assets _{i, t-1}
Ln (COVID per capita)	0.00284* (3.47)	0.00009 (1.95)
RURAL	0.00167 (0.23)	-0.00005 (-0.01)
Ln (COVID per capita) *RURAL	-0.000186*** (-3.94)	-0.000002 (-0.70)
Δ FFR	-3.943*** (-5.84)	-0.0170*** (-0.43)
Δ Ln (Fed Assets)	11.20*** (6.50)	0.0327 (0.32)
Cash/Assets	-0.158*** (-12.99)	-0.001 (-0.75)
Equity/Assets	0.076* (2.11)	-0.004 (-1.71)
Nonaccrual loans / assets	-0.197 (-1.44)	0.001 (0.15)
Net Income / assets	0.099** (3.29)	-0.001 (-0.41)
Interest income / assets	-0.422** (-3.11)	0.007 (0.87)
Ln (assets)	-0.331*** (-48.19)	-0.002*** (-3.91)
Ln (Population)	-0.012 (-1.29)	0.001 (1.01)
Population density	-0.00000823** (-3.03)	-0.00000509*** (-3.20)
Unemployment rate	0.0719*** (7.02)	0.0003 (0.44)
Ln (Stimulus)	0.00031 (0.43)	0.00001 (0.40)
Total Obs. Banks	34046	34046

*Note: The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

I expect that households residing in the U.S county more exposed to the COVID-19 accumulate their funds in core deposits to safeguard them during the pandemic. This is true for core deposits, which are more stable and reflect the confidence of regular customers who see their bank as a reliable safeguard during turbulent times, while brokered deposits indicate funds placed by deposit brokers on behalf of investors. My findings indicate that greater exposure to COVID-19 is associated with a significant rise in core deposits held by banks. As shown by the estimated coefficient presented in Table 2.3, column 1, a 1 percentage increased COVID-19 pandemic exposure led to a 0.28 percentage point rise in banks' core deposits relative to their total assets. In contrast, in column 2 brokered deposits remained unaffected by COVID-19 exposure.

2.5.2 Policy Interaction Effect

Next, I focus on whether the effects of interest rate cuts and quantitative easing on bank deposits were potentially amplified during the COVID-19 pandemic. The results shown previously in Table 2.2 established estimates of the first derivative of deposits with respect to policy and COVID-19 individually, the hypothesis now in question is the degree to which expansionary monetary policy effectiveness impacts banks deposit in areas with high COVID-19 caseloads. Table 2.4, column 1 displays 1 percent increase in per capita COVID cases across counties is associated with 0.32 percentage points increase in Δ Total Deposits/lagged Assets. As compared to the baseline results in Table 2.2, a higher increase in bank deposits is observed.

In Table 2.4, I can also see a negative and significant coefficient on the interaction term between rural indicator and $\ln(\text{COVID per capita})$. The coefficient on the first difference value of the fed funds rate is again statistically significant which indicates transmission of the traditional deposit channel, when the Fed cuts the fed funds rate, deposit inflows are driven by the reduced opportunity cost of holding deposits. I can interpret these results as the fed funds rate is reduced

by 1 percentage point bank deposits increase by 3.181 percentage points (Column 2). This however is based on the $\ln(\text{COVID})=0$ case.

Table 2.4: Impact of COVID-19 on Bank Deposits - Policy Interaction

This table shows how bank deposits reacted to COVID-19 crisis and the role of monetary policy stimulus. Dependent variable is the first difference in total bank deposits divided by the lagged total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Bank and quarter-year fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

Variable	$\Delta\text{Total Deposits}/\text{Total Assets}_{i,t-1}$	
	(1)	(2)
Ln (COVID per capita)	0.0032*** (3.47)	0.0032*** (3.48)
RURAL	0.000133 (0.03)	0.000149 (0.03)
Ln (COVID per capita) *RURAL	-0.000179*** (-5.09)	-0.000180*** (-5.10)
ΔFFR	-3.365*** (-26.33)	-3.181*** (-6.42)
Ln (COVID per capita) * ΔFFR	0.00859* (2.08)	0.00865* (2.09)
$\Delta\text{Ln}(\text{Fed Assets})$	9.164*** (35.25)	8.688*** (6.84)
Ln (COVID per capita) * $\Delta\text{Ln}(\text{Fed Assets})$	0.0225* (2.13)	0.0226* (2.14)
Ln (Stimulus)	-	-0.000200 (-0.38)
Total Obs. Banks	34046	34046

*Note: The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

All considered, my estimated response of bank deposits to a change in the fed funds rate with the effect of COVID-19 cases per capita in column 2 would be interpreted as follows:

$$\frac{\partial(\Delta\text{Total Deposits}/\text{Total Assets}_{ijt-1})}{\partial(\Delta\text{FFR}_{jt})} = -3.181 + 0.00865 * \text{COVID}_{it} \quad (6)$$

$$= -3.181 + 0.00865 * 1 = -3.172$$

In the absence of COVID-19 pandemic, a 1 percentage point reduction in the fed funds rate is associated with an increase in the growth rate of bank deposits by 3.181 percentage points.

However, during the pandemic, a 1 percentage point decrease in fed funds rate increases the growth rate of bank deposits by 3.172 percentage points indicating a slightly less negative impact on bank deposits as compared to other time. This implies that the monetary policy transmission through the deposit channel was not amplified during the pandemic. In other words, unique factors of the pandemic like quantitative easing, fiscal stimulus, precautionary savings and limited opportunities for spending or investment may have overshadowed the impact of the fed funds rate on bank deposits.

When the impact of the Fed asset purchases on deposits is observed, which directly inject liquidity into the banking system, results show that a 1 percent rise in the Fed’s large-scale asset purchase is associated with 8.645 percentage points increase in bank deposits (Column 2).³⁴ This indicates that quantitative easing increased bank reserves and boosted deposits, as this liquidity circulates through the financial system. The estimated response of the bank deposits to a change in the Fed. asset purchases with the effect of COVID-19 cases per capita in Table 2.4, column 2 would be interpreted as follows:

$$\frac{\partial(\Delta Total Deposits/Total Assets)_{jt-1}}{\partial(\Delta Fed Asset_t)} = 8.688 + 0.0226 * COVID_{it} \quad (7)$$

$$= 8.688 + 0.0226 * 1 = 8.714$$

During the pandemic, a 1 percent surge in the Fed asset purchases increases the growth rate of bank deposits by 8.671 percentage points indicating a slightly more positive impact on bank

³⁴ The Fed asset accumulation is measured as log of first difference; therefore, to simplify the results 1 percentage increase in Fed asset purchase is associated with an increase of $8.688 * \log(1.01) \approx 0.08645$ in deposits which is $0.08645 * 100 = 8.645$ percentage points.

deposits as compared to other time.³⁵ According to Castro et al. (2022) large-scale asset purchase including Treasury bonds and mortgage-backed securities by the Fed are one of the factors to explain a surge in bank deposits during pandemic. The scale of quantitative easing was unprecedented and its effect on bank deposits was magnified during the pandemic due to the liquidity needs of households and businesses and banks' desire to hold excess reserves (Drechsler et al., 2024). Therefore, my results also reflect this enhanced role of quantitative easing in deposit growth during the pandemic, as banks accumulated more deposits due to liquidity injections.

In Table 2.4, column 2 I have also included the fiscal stimulus measure (the logarithm of PPP lending) in addition to cyclical and policy variables and expect that fiscal stimulus led to an increase in bank deposit inflow. However, the lack of significance in the result likely suggests the temporary and transactional nature of PPP funds which were meant to be spent quickly rather than stored as deposits.

2.5.3 Policy Interaction Effect by Bank size

This section presents evidence on the COVID-19 outbreak effects on bank deposits when banks are divided into three asset size categories. In Table 2.5, the coefficient on log per-capita COVID-19 cases is significant at the 5% level for small size banks with assets less than 500 million which can be interpreted as 1 percent increase in per capita COVID-19 cases across counties is associated with 0.31 percentage points increase in Δ Total Deposits/lagged Assets. This is consistent with the findings of Li & Strahan (2021) and Dursun-de Neef & Schandlbauer (2020, 2022) that small banks experienced an expansion in their deposits amid the pandemic because

³⁵ The Fed asset accumulation is measured as log of first difference; therefore, to simplify the results 1 percentage increase in Fed asset purchase is associated with an increase of $8.714 * \log(1.01) \approx 0.08671$ in deposits which is $0.08671 * 100 = 8.671$ percentage points.

smaller banks are perceived less risky and more stable compared to larger banks. Thus, depositors may choose to consider moving their funds to smaller banks, viewing them a safe haven during economic uncertainty. Moreover, smaller banks have stronger ties to local communities therefore, customers prefer to keep their funds in banks they know well particularly during uncertain economic conditions (Harris et al., 2021). Laeven et al. (2016) find smaller banks tend to have conservative business practices which are preferred by customers of these banks.

Investigating monetary policy transmission via the deposit channel and quantitative easing on bank deposits for banks with different asset sizes during the pandemic is critical given the significant impact of the monetary policy tools on the banking industry and particularly deposit growth.

The policy response hypothesis indicates a negative and significant coefficient on the fed funds rate for all bank categories. The significant interaction term between COVID-19 cases and the fed funds rate for only the small banks with less than 500 million assets can be interpreted as follows:

$$\frac{\partial(\Delta Total Deposits/Total Assets)_{ijt-1}}{\partial(\Delta FFR_t)} = -3.140 + 0.0143 * COVID_{it} \quad (8)$$

$$= -3.140 + 0.0143 * 1 = -3.126$$

During the pandemic, 1 percentage point decrease in the fed funds rate increase the growth rate of bank deposits by 3.126 percentage points indicating a slightly less negative impact on bank deposits as compared to other time which demonstrates the sensitivity of smaller banks to monetary policy actions. These results align with the findings of d'Avernas et al. (2023) that small banks with less market power and more competition struggle to adjust their deposit rates easily as

compared to larger banks. While large banks can lower deposit rates easily without losing many customers, small banks face greater competitive pressure and must offer relatively higher deposit rates to retain and attract depositors. However, this causes profit margin compression for small banks, as they cannot reduce deposit rates as much as larger banks while also dealing with lower loan rates, ultimately resulting in profitability challenges. Hence, it puts them in a more sensitive position when responding to the fed funds rate cuts.

Bank size also plays a significant role in how quantitative easing impacts growth of deposits of different banks. The results on the log first-difference in the Fed asset purchases as the baseline policy variable indicates an increase in the rate of the Fed asset purchases is associated with bank deposits surge for all bank size categories. In addition, the interaction terms $COVID_{ijt} * \Delta Fedassets_t$ corresponds to my expectations with a positive and significant coefficient but only for banks with assets less than \$500 million. These findings imply that when banks become more exposed to COVID-19, the marginal effect of non-traditional policy response becomes more positive on bank deposits.

$$\frac{\partial(\Delta Total Deposits / Total Assets_{ijt-1})}{\partial(\Delta Fed Asset_t)} = 8.543 + 0.0347 * COVID_{it} \quad (9)$$

$$= 8.543 + 0.0347 * 1 = 8.578$$

During the pandemic, 1 percent increase in the Fed asset purchases increase the growth rate of bank deposits by 8.535 percentage points indicating a slightly more positive impact on bank deposits as compared to other times.³⁶ This suggests that smaller banks experienced a significant

³⁶ The Fed asset accumulation is measured as log of first difference; therefore, to simplify the results 1 percentage increase in Fed asset purchase is associated with an increase of $8.578 * \log(1.01) \approx 0.08535$ in deposits which is $0.08535 * 100 = 8.535$ percentage points.

increase in deposits driven by quantitative easing program during the pandemic which posed both opportunities and challenges for these banks. According to Castro et al. (2022) during the pandemic small banks benefited from an increase in liquidity due to the rise in deposits because of quantitative easing. However, their ability to lend out these funds was constrained. Regulatory requirements, risk management concerns, and reduced demand for loans during the pandemic limited how smaller banks could use these deposits. Additionally, the expansion of deposits outpaced the banks' ability to generate profitable lending opportunities, which is a common issue with quantitative easing policies.

Table 2.5: Impact of COVID-19 on Bank Deposits - Policy Interaction by Bank Size

This table shows how bank deposits reacted to COVID-19 crisis and the role of monetary policy stimulus. Dependent variable is the first difference in total bank deposits divided by the lagged total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Banks are divided into three asset size categories. Bank and quarter-year fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

Variable	Δ Total Deposits/Total Assets _{i, t-1}		
	(1) Assets<500M	(2) 500M<Assets<1B	(3) Assets>1B
Ln (COVID per capita)	0.0031** (2.99)	0.0011 (0.49)	0.0020 (0.62)
RURAL	-0.00158 (-0.29)	-0.0321 (-1.54)	0.0225 (1.34)
Ln (COVID per capita) *RURAL	-0.000184*** (-4.69)	0.000200 (1.91)	0.0000249 (0.17)
Δ FFR	-3.140*** (-5.75)	-3.363*** (-2.93)	-3.475*** (-2.19)
Ln (COVID per capita) * Δ FFR	0.0143** (3.15)	-0.0103 (-0.99)	-0.0260 (-1.73)
Δ Ln (Fed Assets)	8.543*** (6.13)	9.975*** (3.38)	10.43*** (2.54)
Ln (COVID per capita) * Δ Ln (Fed Assets)	0.0347** (3.00)	-0.0255 (-0.91)	-0.0856* (-2.17)
Ln (Stimulus)	-0.000149 (-0.26)	0.000438 (0.36)	0.000305 (0.18)
Total Obs. Banks	23709	4588	5749

*Note: The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

The fiscal stimulus measure (the logarithm of PPP lending) does not show significant results for any of the banks size categories in my results. Studies like Karakaplan (2021) suggests that small banks played a critical role in distributing PPP loans and maintaining strong relationships with local businesses during the pandemic. Moreover, small community banks outperformed large banks in PPP lending, participating in PPP lending.³⁷ When banks disburse PPP loans, the funds are deposited into business accounts, increasing deposits temporarily. However, these funds are meant to be used for operational costs, such as payroll, meaning they do not necessarily stay in the deposit system for long periods. Thus, the temporary nature of these deposits explains why banks, particularly small banks, have not reflected an increase in deposit inflows in the results. These results are consistent with Li & Strahan (2021) that banks, particularly smaller community banks, engaged in relationship lending through the PPP and the nature of these loans and the related inflows to deposits were transitory.

2.5.4 Bank Capitalization for Small Banks

Finally, I have subdivided only small banks, which rely heavily on deposit funding, into three capital leverage ratio groups: $< 8\%$ (undercapitalized), $\geq 8\%$ and $< 10\%$ (adequately capitalized), and $\geq 10\%$ (well capitalized) which is important to consider how different levels of capital adequacy influence ability of banks to manage deposits and financial stability. During the COVID-19 pandemic, there were regulatory adjustments related to capital requirements that were designed to ensure that banks could continue lending and supporting the economy during the crisis, even as they faced significant pressure from increased deposits and potential losses on loans.

³⁷ <https://www.americanbanker.com/news/participating-in-ppp-increased-banks-risk-appetite-study-finds>

Therefore, Table 2.6 demonstrates that only small and well-capitalized banks observed a surge in deposits. Well capitalized banks are perceived less risky by consumers, so they deposit their funds in these banks because they can absorb losses during high uncertainty periods. The coefficient on log per-capita COVID-19 cases is significant at the 1% level for small well-capitalized banks. This is consistent with Peek & Rosengren (1995) finding that better-capitalized banks are more equipped with handling bad times, so they experience a rapid increase in deposit inflows than poorly capitalized banks.

Table 2.6: Impact of Covid-19 on Bank Deposits - Bank Capitalization

This table shows how bank deposits reacted to COVID-19 crisis and the role of bank capital. Dependent variable is the first difference in total bank deposits divided by the lagged total bank assets. Log COVID per capita is the natural logarithm of 1 + the bank-level exposure to COVID-19 case counts where COVID-19 case exposure is the deposit weighted number of new COVID-19 related cases divided by 100,000 individuals during a quarter in a U.S county. Estimation sample is 2019Q1 – 2021Q1. Banks are divided into three asset size and capital ratio categories. Bank and quarter-year fixed effects are included. The robust standard errors clustered at the bank level are reported under the coefficients.

Variable	Δ Total Deposits/Total Assets _{i, t-1}		
	(1) Assets<500M (Capital Ratio<0.08)	(2) Assets<500M (0.08≤Capital Ratio<0.10)	(3) Assets<500M (Capital Ratio≥0.10)
Ln (COVID per capita)	0.0014 (0.22)	-0.0008 (0.45)	0.0038*** (3.41)
RURAL	0.0272 (0.44)	0.00783 (0.22)	-0.00103 (-0.21)
Ln (COVID per capita) *	-0.000868**	-0.000201**	-0.000111*
RURAL	(-3.05)	(-2.83)	(-2.50)
Δ FFR	-7.760* (-2.36)	-3.519*** (-4.46)	-3.038*** (-4.68)
Ln (COVID per capita)	0.0148	-0.00317	0.0152**
* Δ FFR	(0.49)	(0.37)	(3.14)
Δ Ln (Fed Assets)	20.33* (2.44)	10.03*** (5.03)	7.681*** (4.62)
Ln (COVID per capita) * Δ Ln (Fed Assets)	0.0374 (0.47)	-0.00662 (-0.31)	0.0338** (2.73)
Ln (Stimulus)	0.00361 (1.05)	-0.000279 (-0.34)	-0.000237 (-0.35)
Total Obs. Banks	1113	7320	16390

*Note: The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

The conventional policy variable again indicates the expected coefficient on the fed funds rate for all capital-ratio groups. In addition, the interaction term between COVID-19 cases and the fed funds rate determines a positive and significant coefficient on the interaction term for only small well-capitalized banks. In the absence of COVID-19 pandemic, 1 percentage point reduction in fed funds rate is associated with an increase in the growth rate of bank deposits by 3.038 percentage points. However, during the pandemic, 1 percentage point decrease in the fed funds rate increase the growth rate of bank deposits by 3.023 percentage points indicating a slight less negative impact on bank deposits. This can be interpreted as deposits of small well-capitalized banks show a greater sensitivity to conventional expansionary policy during the pandemic.

If we compare Table 2.5 and 2.6, we can see the magnitude of the coefficient on interaction term between COVID-19 cases, and the fed funds rate is high for banks with highest capital ratio (≥ 0.10). Small banks rely heavily on deposit funding, therefore, change in monetary policy that affects deposit rate directly impacts bank deposits of these banks. Although there is pressure on small banks to compete with larger banks by maintaining relatively higher deposit rates, these small banks can attract deposit inflows due to their reputation for safety. As noted by Li et al. (2020), small banks acted as crucial financial intermediaries during the pandemic, benefiting from the increased demand for deposit security when interest rate declined. However, well-capitalized small banks are more responsive to interest rate changes because their equity capital gives them buffer to adjust the change in deposit rate quickly. Moreover, the monetary policy transmission is more pronounced for small banks with more equity capital because these banks are often perceived safer because they are more risk averse, have strong capital base and conservative banking practices (Bernanke et al., 1991; Kashyap & Stein, 1995). Therefore, my results confirm that the effect of the fed funds rate cut during the crisis period is stronger on banks with high capital-ratio.

Moreover, Table 2.6 shows a positive and significant coefficient on log first-difference in the Fed asset purchases for all capital-ratio groups. However, the interaction terms $COVID_{ijt} * \Delta Fedassets_t$ which corresponds to my expectations with a positive and significant coefficient is only for small and well-capitalized banks. Results indicate that 1 percent increase in the Fed asset purchases increase the growth rate of bank deposits by 8.535 percentage points indicating a slightly more positive impact on bank deposits as compared to other time.³⁸ These findings imply that when banks become more exposed to COVID-19, the marginal effect of quantitative easing on bank deposits becomes stronger when banks are equipped with high capital. This implies that banks with robust capital buffer during the time of uncertainty like the pandemic are better equipped to benefit and handle the inflow of liquidity generated by quantitative easing. Well-capitalized banks can absorb risk more effectively and extend additional lending, which in turn amplified the inflow of deposits. This process was particularly critical during the pandemic, as the combination of quantitative easing and capital relief policies enabled these banks to effectively manage the surge in deposits without compromising their capital adequacy.

In summary, the interest rate cuts provided short-term incentives for depositors to flock to stable institutions like well-capitalized small banks, while quantitative easing flooded the system with liquidity, further enhancing deposit inflows.

Table 2.6 also controls for PPP fiscal stimulus which is crucial because it reveals how government interventions like PPP can disproportionately benefit certain segments of the banking sector, particularly small banks with strong capital buffers. During the COVID-19 pandemic, PPP

³⁸ The Fed asset accumulation is measured as log of first difference; therefore, to simplify the results 1 percentage increase in Fed asset purchase is associated with an increase of $8.578 * \log(1.01) \approx 0.08535$ in deposits which is $0.08535 * 100 = 8.535$ percentage points.

lending had a notable impact on bank deposits, particularly for small and well-capitalized banks. These institutions were better equipped to manage the temporary influx of deposits stemming from PPP loans due to their stronger capital positions, which allowed them to absorb liquidity effectively. The nature of PPP loans, however, was temporary, which meant that while these banks experienced short-term boosts in core deposits and lending activity, the long-term impact on their financial stability was minimal. Despite the initial inflow of deposits, the transient nature of these loans limited any long-lasting effects on bank deposit structures, as reflected in Anbil et al. (2023). They suggest, the temporary nature of PPP loans, combined with the more sustained effects of quantitative easing and precautionary savings, meant that the longer-term changes in bank balance sheets were driven by these broader factors rather than the PPP lending alone.

2.6 Conclusion

This paper explores why U.S. commercial banks experienced a surge in deposits inflows during the COVID-19 pandemic. To examine the view to consider banks as a safe-haven, my paper investigates whether households moved their savings to banks on the onset of the COVID-19 pandemic which resulted as an increase in bank deposits. The findings of my paper are consistent with the literature which shows that banks are seen as a safe haven during crises (see, e.g. Dursun-de Neef & Schandlbauer, 2020, 2022; Gatev et al., 2009; Gatev & Strahan, 2006). In analyzing the extent to which the Federal Reserve's monetary policy actions impacted the growth of bank deposits in the U.S. during the pandemic, the results show that lowering interest rates and implementing quantitative easing significantly contributed to the growth of bank deposits. While interest rate cuts played a role by encouraging savings through the deposit channel of monetary policy, results suggest that the effect of quantitative easing was more substantial in boosting bank deposits by improving the liquidity position of banks and ensuring they can handle increased

deposits. Moreover, this study examines the effect of PPP fiscal stimulus on bank deposits. Aligned with literature (see, e.g., Karakaplan, 2021; Li & Strahan, 2021), my results find that PPP funds did not significantly contribute to a surge in bank deposits which reflects the transitory nature of PPP funds which were meant to be spent quickly rather than stored as deposits. When the geographical impact of COVID-19 cases per capita on bank deposits is observed, my paper concludes that banks located in rural areas experienced a smaller increase in their deposits during the pandemic as compared to their urban counterparts.

However, when I categorize the banks in different asset sizes to find which banks are seen as a safe haven during COVID-19 pandemic, the results show that a significant increase in deposits is only observed for the small banks, which is due to their strong customer relationship and preference of these customers to choose small banks with conservative business practices (Harris et al., 2021; Laeven et al., 2016). Furthermore, when banks are categorized in asset sizes, expansionary monetary policy with the fed funds rate cut and quantitative easing, was able to contribute to a sustained growth in deposits with the rising local COVID cases per capita for all bank size categories which gives a proof of successful transmission of expansionary monetary policy for the financial stability of the economy during the crisis period (see, e.g. Agarwal et al., 2021; Cúrdia, 2020). I also find that only small banks are more sensitive to the monetary policy transmission (see, e.g. Kishan & Opiela, 2000) during crisis period as these banks have less market power and more competition so they struggle to adjust their deposit rates easily as compared to larger banks and these banks also experienced more liquidity due to rise in deposits because of quantitative easing.

Finally, when only small banks are subdivided into three capital leverage ratio groups, I find that small well-capitalized banks with less than \$500 million assets experienced a surge in deposits during the pandemic as they are better equipped with capital to handle crisis periods. When the transmission of monetary policy on deposits is inspected for such banks, results suggest that small well-capitalized banks are more sensitive to expansionary policy because their customers consider them a safe place based on their capital positions during the pandemic.

My analysis comprised of the impact of monetary policy on bank deposits during the COVID-19 pandemic can be subject to several limitations. For example, the bank balance sheet data is available on quarterly basis which do not cover short-term fluctuations in deposits within each reporting period and the sudden shifts in deposits within each quarter can get averaged out which limits the ability to capture the immediate responses. Moreover, the rapid adoption of digital banking during the pandemic may have influenced deposit patterns in ways not captured in this study. Future research may address these limitations by using higher-frequency datasets such as weekly, daily, or monthly bank level data to better capture immediate responses and volatility in deposit flows. In addition, future studies can examine how technology adoption affected deposit flows by comparing banks with different levels of digitalization.

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Appendix B

Appendix Table 2.1: Variable List from the Call Reports

Variable	Source	Code
Total Deposits	Call Reports	RCON2200
Total Core Deposits	Call Reports	RCON6631+RCON6636+ RCON0352+RCONj473
Total Brokered Deposits	Call Reports	RCON2365
Total Assets	Call Reports	RCON2170
Total Equity Capital	Call Reports	RCON3210
Total Nonperforming Loans	Call Reports	RCON1407
Total Net Income	Call Reports	RIAD4340
Total Cash	Call Reports	RCON0071
Total Interest Income	Call Reports	RIAD4107

Appendix Table 2.2: Fed Buys Securities from a Nonbank entity (QE creates deposits)

1) Before Transaction

Federal Reserve	
Assets	Liabilities
-	-

Commercial Bank A	
Assets	Liabilities
Reserves: \$100	Deposits: \$500
Securities: 0	-

Nonbank Seller	
Assets	Liabilities
Treasury Bond: \$100	-
Deposit: 0	-

2) After the Transaction

Federal Reserve	
Assets	Liabilities
Treasury Securities: +\$100	Reserves (Bank A): +\$100

Commercial Bank A	
Assets	Liabilities
Reserves: \$200 (↑ \$100)	Deposits: \$600 (↑ \$100)
Securities: 0	-

Nonbank Seller	
Assets	Liabilities
Deposit: \$100	-
Treasury Bond: 0	-

Appendix Table 2.3: Fed Buys Securities from a bank (No deposits created)

1) Before Transaction

Federal Reserve

Assets	Liabilities
-	-

Commercial Bank A

Assets	Liabilities
Reserves: \$100	Deposits: \$500
Treasury Securities: \$100	-

2) After the Transaction

Federal Reserve

Assets	Liabilities
Treasury Securities: +\$100	Reserves (Bank A): +\$100

Commercial Bank A

Assets	Liabilities
Reserves: \$200 (↑ \$100)	Deposits: \$500 (no change)
Treasury Securities: 0	-

Appendix Figure 2.1 Fed Asset Purchase from Nonbank (Deposits Increase)

Fed Asset Purchase from Nonbank

(1) Fed buys Treasury from a Nonbank Seller (e.g., mutual fund, household)

↓

↓ sells \$100 security

(2) Federal Reserve pays by adding reserves to Bank A

Federal Reserve

Assets: +\$100 Treasury

Liabilities: +\$100 Reserves (Bank A)

↓

↓ +\$100 reserves

(3) Bank A credits the nonbank seller's deposit

Bank A (Commercial Bank)

Assets: +\$100 Reserves

Liabilities: +\$100 Deposits

↓

↓ +\$100 deposit

(4) Nonbank Seller now holds a bank deposit

Nonbank Seller

Assets: +\$100 Deposits

Assets: -\$100 Treasury

- Fed balance sheet expands (Treasuries ↑, Reserves ↑)
- Bank A balance sheet expands (Reserves ↑, Deposits ↑)
- Bank balance sheet expands
- Fed balance sheet expands

Appendix Figure 2.2 Fed Asset Purchase from a Bank (No New Deposits Created)

Fed Asset Purchase from a Bank

(1) Fed buys Treasury directly from Bank A

Bank A

↓ sells \$100 Treasury to Fed

(2) Federal Reserve credits Bank A's reserve account

Federal Reserve

Assets: +\$100 Treasury

Liabilities: +\$100 Reserves (Bank A)

↓

(3) Bank A replaces one asset with another

Bank A (Commercial Bank)

Assets: -\$100 Treasury

+\$100 Reserves

Liabilities: Deposits (Unchanged)

- Fed balance sheet expands (Treasuries ↑, Reserves ↑)
- Bank A balance sheet is the same size (Only composition changes)
- No new deposits are created
- Reserves increase but deposits stay the same

3. The Relationship Between Interest Rates and Bank Profitability: Evidence from a Dynamic Panel Threshold Analysis

3.1 Introduction

The relationship between interest rates and bank net interest margin (NIM) is an important area of study in financial economics, particularly in understanding how banks navigate different economic environments. NIM, a key performance indicator for banks, represents the gap between the interest income earned and the interest expense incurred by the bank, relative to the amount of their interest-earning assets. The fluctuation of interest rates, governed largely by monetary policy, significantly impacts NIM, influencing bank profitability and stability. One of the key factors influencing NIM is the prevailing interest rate environment, as fluctuations in interest rates directly affect both a bank's lending capabilities and borrowing costs. In the context of the U.S. economy, understanding this relationship is particularly critical given the Federal Reserve's active role in interest rate adjustments to achieve monetary policy objectives. While extensive research has explored the effects of interest rate changes on bank profitability, there remains a gap in understanding the specific thresholds at which these changes significantly impact NIM. This research aims to identify the threshold level of interest rates beyond which their influence on banks' NIM becomes notably stronger or weaker, providing valuable insights into the conditions under which banks experience increasing or declining profitability.

Existing literature suggests that the impact of interest rates on NIM can differ significantly between low and high-interest rate environments. Generally, as interest rates decrease, the cost of borrowing declines. Thus, lower borrowing costs allows more consumers and businesses to borrow and spend or invest in infrastructure. In this case, the outcome may be a growing economy and prosperity. However, banks often experience a compression of NIM due to a limited ability to

reduce funding costs further, particularly as deposit rates approach zero. This phenomenon, referred to as the "zero lower bound effect," constrains the spread between lending and deposit rates, adversely affecting bank profitability (Claessens et al., 2018; English et al., 2018). The persistence of low interest rates further adversely impacts bank profitability which comes at the expense of lenders and savers, therefore impacting returns of banks, as their funding from deposits decreases, and consumers, as their savings or investments of similar nature also return less. The market events raised concerns among economists about the effectiveness of expansionary monetary policy, especially under low-interest rate conditions, to stimulate the economy. One possible explanation is that when the policy rate falls below a certain level and NIMs are compressed, banks' fall short in their role of passing on the benefits of a lower interest rate to the real economy (Brunnermeier & Koby, 2019).

Conversely, in a high-interest rate environment, the dynamics change substantially. In periods of high-interest rates, banks typically benefit from a wider spread between the rates they charge borrowers and the rates they pay depositors. This scenario often results in an increase in NIM, as higher rates generally lead to higher yields on loans and investments compared to the costs of funding. So, it is commonly believed that rising interest rates are associated with increase in net interest income contributing to an increase in NIM and enhanced profitability in the banking system (Ho & Saunders, 1981; Maudos & Fernández de Guevara, 2004). However, the directional impact of rising interest rates on NIM is subject to theoretical ambiguity because the funding costs faced by the banks may rise either faster or slower than its return on interest earning assets. As interest rate increase, banks may face higher interest cost by paying higher interest rate on some portion of their deposits or other liabilities to attract or keep funding; some portion of the bank's assets, meanwhile, will continue to yield their contractual interest rates and therefore not reprice

upward (Bernanke & Gertler, 1995; King & Levine, 1993). As highlighted in the Financial Stability Oversight Council's Annual Report (2022), a sharp rise in interest rate may reduce bank profitability with a greater proportion of longer-term fixed-income securities or mortgage loans.³⁹ Theoretically, the interest income effect is one of the notable impacts of interest rate changes on banking performance. The interest income effect captures how fluctuations in interest rates affect net interest income. If banks involve in maturity transformation by borrowing short term and lending long term, then an interest rate hike is expected to increase interest expenses relative to interest income, reducing NIM. In contrast, if the pass-through from market interest rates to deposit interest rates is sluggish and bank originate a substantial portion of assets amid elevated interest rates, then NIMs increase. Therefore, theoretically the interest income effect may either decrease or increase NIMs.

Building on recent empirical findings the relationship between interest rates and NIM is nonlinear, with evidence indicating that banks respond differently to interest rates change depending on the prevailing interest rate environment (Claessens et al., 2018; English et al., 2018). These stylized facts point toward the existence of a threshold effect where the impact of interest rates on bank margins changes depending on whether rates are above or below a critical level. The economic rationale for this threshold behavior lies in banks' maturity transformation role (English et al., 2018; Borio et al., 2017). In low-interest rate environment, banks' loan yields tend to decline more quickly than their funding costs due to sticky deposit rates, compressing margins. In contrast, in high-rate environment, funding costs reprise more quickly, and loan yields adjust more gradually beyond a certain point.

³⁹ <https://home.treasury.gov/system/files/261/FSOC2022AnnualReport.pdf>

This consideration underscores the relevance of my research for central bankers, as it is important for them to consider the impacts of the interest rate on banks' NIM to evaluate the likely impact of their policy measures. Hence, this paper is intended to produce meaningful insights and knowledge for individuals, policy makers, and institutions, making it possible for them to manage more effectively the changes in the interest rate environment. Although a substantial body of literature suggests that low interest rates are positively associated with NIMs (Claessens et al., 2018; Borio et al., 2017; Busch & Memmel, 2017), no definitive conclusion is established with respect to the level at which interest rates are no longer viewed as low. The prevailing view holds that within the low-interest rate environment a change in the level of interest rates results into an effect on bank profitability different than it would have in a 'normal' or 'higher' interest rate environment (Ampudia & Van den Heuvel, 2022). On this basis, I will investigate the 'tipping point' of the non-linear relationship between interest rates and bank NIM. Once this has been empirically determined, it will be used as a 'threshold' by which interest rates will either be considered 'high', if above, or "low", if below.

This study is conducted to evaluate the impact of interest rates on bank NIM within the context of the U.S. economy, employing a dynamic panel threshold model as proposed by Seo & Shin (2016). This model is particularly suitable for capturing non-linear relationships and threshold effects, which are crucial for understanding how different interest rate environments impact bank performance. While previous studies (e.g., Borio et al., 2017; Ampudia & Van den Heuvel, 2022) have explored the nonlinear relationship between interest rates and bank profitability, this research extends the analysis by identifying a specific threshold of short-term interest rate where the impact of rate changes reverses. With the application of the dynamic panel threshold model, the study provides empirical evidence of how the magnitude and direction of interest rate effects vary across

environments, offering nuanced insights into the asymmetry in NIM dynamics. Existing studies often analyze broader banking sectors or focus on European or global contexts (e.g., Claessens et al., 2018; Delis & Kouretas, 2011). But this study contributes to the specific literature on U.S. commercial banks, highlighting the unique interplay of their funding structures, loan portfolios, and regulatory environments in determining profitability across interest rate environments.

Having established a statistically significant endogenous threshold of short-term interest rate as one of the contributions to the literature, my findings show that there is a nonlinear relationship between short term interest rate and banks' NIM. Particularly, the threshold value of short-term interest rate is 2.82%, determining the low and high-interest rate environments. In the low-interest rate environment, the bank's NIM decreases when the short-term interest rate decreases because loan yields fall while deposit rates are already near their lower bound and cannot adjust downward, compressing margins. Conversely, an increase in the short-term interest rate raises NIM, as loan yields rise but deposits costs remain relatively sticky. In the high-interest rate environment, the pattern reverses: a decrease in short-term interest rate increases NIM because funding costs fall more quickly than loan yields and borrowing becomes more affordable, whereas an increase in the short-term interest rate reduces NIM due to faster repricing of funding costs.

Further, this study is the first to also investigate the interest rate threshold effects on NIM for both community and non-community banks in the U.S. It provides novel insights into the nonlinear relationship between interest rates and NIM across these distinct banking segments, addressing a critical gap in the literature. Community banks, which tend to have closer relationships with their customers and a localized market focus, may respond differently to interest rate changes compared to non-community banks, which operate on a broader scale and have more diversified portfolios. Community banks, typically smaller banking entities with assets less than

\$1 billion, that serve localized markets, often rely heavily on relationship-based banking, where personalized services and local knowledge contribute significantly to their operations (Berger & Udell, 2002). Since community banks rely heavily on traditional interest income from lending and deposits it makes them more sensitive to fluctuations in interest rates (Hanauer et. al, 2021). In fact, one of the challenges community banks faces is due to interest rates fluctuations which can significantly impact their net interest margins and overall profitability, given their reliance on traditional banking activities. For instance, in a low-interest rate environment, narrow interest margins make it challenging to maintain profitability. However, in a high-interest rate environment, rising funding costs, especially for deposits, can outpace asset yield growth which compresses margins. This reliance limits their ability to diversify revenue streams. According to FDIC (2021) the NIM of a typical community bank has exhibited a positive co-movement with the federal funds rate, but this relationship has been much less pronounced for banks with high concentrations of long-term assets. Community banks traditionally hold a higher share of long-term assets to total assets relative to non-community banks. In contrast, non-community banks, which tend to be larger and operate across broader geographic areas, have more sophisticated risk management practices and a diversified portfolio of services. DeYoung & Rice (2004) show that these large banks generate more noninterest income as a fraction of operating revenue than community banks do. Given these structural differences, the relationship between interest rates and NIM may vary significantly between community and non-community banks, warranting a detailed comparison in this study. By examining these differences, the research explores whether the threshold of short-term interest rates that influences NIM differs between these two types of banks, considering their distinct business models. By identifying these thresholds, the study aims

to provide insights into how banks can better manage their interest rate risk in varying economic conditions.

In summary, this paper contributes to the literature on a number of margins. Firstly, the paper documents a threshold level of short-term interest rate to determine the low and high-interest rate environment to examine the relationship between NIMs and short-term interest rates using the novel approach of dynamic panel threshold model of Seo & Shin (2016). This methodology has several advantages as compared to traditional approaches commonly found in the existing literature. One important aspect of the dynamic panel threshold regression is that it is capable of capturing nonlinearity by identifying the threshold value where the direction of the relationship between interest rate and bank profitability changes significantly. Standard linear regression models are unable to account for such threshold effects and lead to biased estimates. In the literature quadratic models are also included to investigate threshold effects to capture nonlinearity between interest rate and NIM but they may suffer from multicollinearity so they cannot account for asymmetric effects as effectively as threshold models. Moreover, this approach identifies and estimates the threshold value accurately and offers exact cut off values and significance level which in turn improves our understanding of the dynamics of the relationship between short-term interest rate and NIM. Additionally, this dynamic panel threshold model employs a GMM based estimator which deals with the problem of endogeneity that specifically arises from the inclusion of lagged NIM as an explanatory variable and captures the dynamic behavior of bank profitability. Furthermore, relative to prior threshold models, this approach enables both the threshold variable and other regressors to be endogenous which allows a more realistic framework for financial data. This method also captures the heterogeneous impact of explanatory variables across regimes, rather than estimating common effects across regimes. Bolarinwa et al. (2021) in their study emphasized

that the dynamic panel threshold model developed by Seo & Shin (2016) provides robust and efficient estimates in the presence of endogeneity, heteroscedasticity, and simultaneity which improves the robustness of estimation outcomes.

Secondly, to the extent of my knowledge this research is the first to identify and estimate a threshold in the relationship between short-term interest rates and bank net interest margins (NIM) within the context of the U.S. banking sector. While previous research has documented nonlinearities in the interest rate–bank profitability relationship, none have explicitly estimated a regime-dependent threshold that differentiates the effects of interest rate changes across low and high-interest rate environments. By applying the dynamic panel threshold model of Seo & Shin (2016), this study not only uncovers the existence of a critical threshold of short-term interest rates in the U.S. economy but also provides empirical evidence that the magnitude and direction of interest rate effects on bank profitability differ significantly across environments. This novel contribution enhances the existing literature by offering new insights into how monetary policy affects banks differently depending on the interest rate environment.

Thirdly, by identifying threshold effects and non-linearity, the study offers valuable implications for policymakers and bank managers in formulating strategies to navigate different interest rate environments effectively. Fourthly, by examining the threshold effect of short-term interest rates on bank NIM, this is the first study with distinguishes between community and non-community banks to offer insights into how their distinct business models and risk exposures lead to differential responses of bank profitability to interest rate changes.

The structure of the paper is as follows: The literature addressing the effects of interest rates on banks' NIMs is outlined in section 2, section 3 provides an overview of the data source

and description, section 4 focuses on the empirical approach, section 5 shows results and section 6 concludes.

3.2 Literature Review

Several studies explore the relationship between interest rates and bank profitability (such as Borio et al., 2017; Claessens et al., 2018; Brei et al., 2020; Genay & Podjasek, 2014; Alessandri & Nelson, 2015, etc.). However, it is still an under-researched area and hence there is no clear consensus among researchers on whether the interest rate has positive, negative, or no effect on the performance of banks. As a country-specific study, my chapter contributes to the literature by further exploring the relationship between bank profitability and interest rate changes by filling the gap in understanding whether the low and high-interest rate environments change the relationship between interest rates and NIM using a threshold empirical methodology.

Low interest rates may act as stimulus for economic expansion; however they may also compress banks' NIM. A bank's NIM represents the margin between interest income from lending activities and interest expenses incurred on deposits, relative to total interest-earning assets held by a bank. Several prior studies based on cross-country data document a positive yet non-linear association between interest rates and banks' net interest margins, with low interest rates exerting a stronger impact on banks' net interest margins than high rates (Borio et al., 2017; Claessens et al., 2018; Brei et al., 2020).

Evidence from individual country analyses confirms the stronger adverse impacts of low interest rates on NIMs. For instance, Bikker & Vervliet (2018) analyze the soundness of banking system in the U.S. by exploring the effect of low interest rates on bank profitability. Their balance sheet data acquired from the quarterly Call Reports from 2006 to 2015 covers the period of before

and after the financial crisis. Using System GMM their findings suggest that banks' NIMs decline with the lower interest rates. Their paper finds a non-linear effects of both the level of interest rate and the yield curve slope on bank NIMs. They find that the interest rates' impact on the bank profitability is stronger when interest rates are low.

Similarly, Genay & Podjasek (2014) explicitly study the impacts of interest rates on bank profitability and find detrimental impacts of low interest rates on NIMs. Their findings suggest sustained low interest rates adversely impact U.S. banks through a reduced interest rate spread. Using Call Reports data of 5,583 commercial banks from 2003:3 to 2013:2, their Generalized Method of Moments model estimates the impact of changes in interest rates on commercial banks' profitability which relates banks' NIMs and return on assets to changes in the three-month U.S. treasury bill (T-bill) interest rate, as well as in the yield curve. Their findings suggest that banks demonstrated greater ability to compensate the adverse effect of low interest rates on profits by changing their business practices e.g., charging higher fee and lower loan loss provisions.

Aligned with the previous findings as well as Alessandri & Nelson (2015), a positive relationship between net interest margin and short-term interest rate is found. As interest rates rise, banks increase their loan rates and lower the volume of extended credit, possibly through the adoption of more conservative lending policies and vice versa. With respect to the yield curve, empirical evidence suggests that bank income margins tend to expand when the yield curve steepens, reflecting the maturity transformation banks perform by borrowing short and lending long. To evaluate these proportions, the authors use a panel data for UK and foreign banking groups operating in the UK from 1992 to 2009.

A few cross-country studies have explicitly examined whether changes in interest rates exert differential impact on banks' NIMs and profitability when interest rates are low. Borio et al. (2017)

discover the association between monetary policy and bank profitability with a specific emphasis on the relationship between interest rates and bank profitability using a comprehensive sample of international banks. One of the main contributions of their research incorporates a dataset that includes 109 large international banks headquartered in 14 advanced economies from 1995 to 2012. The authors report substantial non-linearities in the relationship between the interest rate structure and bank profitability which suggests a compression of NIM when the interest rates are reduced to very low levels. They find a 100-basis points drop in interest rates causes a 25-basis points fall in banks profitability after one year, with the magnitude of this effect reaching up to 40 basis points when interest rates are very low.

In addition, according to Claessens et al. (2018) the relationship between interest rate and NIMs may exhibit non-linearity. Therefore, to distinguish between the general effects of interest rate changes and those that occur when the interest rate is low is crucial. One of their main contributions to the literature is that they explore the differential effect of interest rates changes on bank NIMs by classifying countries each year as being in a low- or high-rate environment depending on whether the yield on the three-month sovereign bond exceeds or fall below 1.25 percent. Employing a dataset containing 3385 banks from 47 countries from the period 2005 to 2013, the authors report that low interest rates adversely affect bank profits as one percentage point decline in interest rates imply an 8-basis points lower NIM as compared to high interest rates. Moreover, in a low-interest rate environment for 4 years the bank profitability is 25-30 basis points lower. This means it is possible that lowering the interest rates for a longer duration leads to further reduction in NIM and profitability.

However, further evidence indicates that low interest rates have no significant impact on banks' NIMs. Altavilla et al. (2018) use an unbalanced sample of 288 European banks and find

that a flattening of the yield curve and lower interest rates are not linked to reductions in NIMs after controlling for prevailing and anticipated economic and financial conditions. Moreover, Scheiber et al. (2016) analyze aggregated bank balance sheets to examine the effect of ultra-low and negative interest rates in Denmark, Sweden, and Switzerland on bank profitability from 2010:1 to 2015:4. Results show that low interest rates have not yet led to a significant decline in bank profits. For these countries, this is mainly because net interest income did not decline and remained statistically significant. However, the findings suggest if negative interest rates persist over an extended period, this in turn may eventually decrease banks' profitability. But raising lending volume can compensate for lower profit.

There are some studies claiming a positive influence of low interest rates on bank profitability in the literature. For example, Jobst & Lin (2016) evaluate the effect of negative rates on bank profitability and its role in shaping monetary transmission mechanisms in the Euro Area during periods of limited responsiveness in deposit rate adjustments using a general equilibrium specification. They estimate DSGE model using euro area data. The findings show a statistically significant small but positive effect of low interest rates on NIM, a 0.5% decline in the policy rate corresponds to a 0.07% increase in NIM. They claim that many banks offset the falling interest revenue due to negative rates by increasing the loan volumes. However, they expect a negative influence on NIM in the future if the interest rates would be lowered again.

It is generally believed that banks tend to favor higher interest rates, and certainly higher rates on loans and investments lead to higher bank revenues. However, banks must finance their investments and face higher funding costs when market rates are high. Most banks finance their lending and other investment activities by issuing debt, primarily through customer deposits, but also through various securities sold in the open market. An increase in interest rates is typically

accompanied by higher funding costs for banks. Consequently, whether higher interest rates lead to wider or narrower NIMs remains ambiguous, as the relationship depends on how both income and expense components adjust.⁴⁰

The impact of short-term interest rates on NIM is theoretically ambiguous and driven by various banking and economic factors. It is commonly believed that higher short-term interest rates contribute to higher net interest income, which leads to an increase in NIM. This raised concerns about bank profitability when interest rates remained low for an extended period starting in 2008. However, the directional impact of rising interest rates on NIM is theoretically ambiguous due to the possibility that the funding cost incurred by a bank may increase more rapidly or more slowly than its return on earning assets. Rising interest rates force banks to offer higher interest rates on certain deposits or other liabilities in order to retain or secure funding, while some assets remain locked into lower contractual interest rates and consequently not reprice upward. Periods of rising interest rates frequently align with strong economic conditions, during which banks typically increase lending, and the resulting increase in the composition of loans relative to investments tends to raise the average yield on assets. Simultaneously, an expansion in lending necessitates an increase in bank funding. To meet increased funding needs, banks offer higher interest rates on deposits to attract new funds or use alternative funding channels with higher associated costs. These potentially offsetting effects contribute to the theoretical ambiguity surrounding whether NIM expands or compresses in response to higher interest rates.

In recent years, an increasing number of single-country and cross-country studies have tried to quantify the causal effect of interest rates on bank profitability, controlling for other factors.

⁴⁰ <https://www.stlouisfed.org/on-the-economy/2016/may/banks-more-profitable-interest-rates-high-low>

Causal effects are most commonly estimated with dynamic panel regressions namely Generalized Methods of Moments (GMM) models, tracking data on multiple banks through time. Within the context of these dynamic regression models, bank profitability is regressed against its lagged value, the short-term interest rate or long-term interest rate and yield curve slope. Additional covariates are also incorporated to account for both individual bank characteristics and macroeconomic conditions that impact bank profitability. It is suggested that several issues need to be considered while using dynamic panel data models (Bikker & Vervliet, 2018). For example, some bank profitability determinants are possibly of endogenous nature and create reverse causality between dependent and independent variable. Moreover, unobserved heterogeneity which is possible due to some fixed effects specific to each individual bank can impact the bank's profitability. Therefore, by using GMM models the issue of endogeneity and unobserved heterogeneity are controlled. These dynamic bank probability models are widely acknowledged in the existing empirical literature (see, e.g., Bikker & Vervliet, 2018; Genay & Podjasek, 2014; Alessandri & Nelson, 2015; Borio & Gambacorta, 2017; Claessens et al., 2018). Despite the commonality in the approach, findings in the literature vary considerably.

Although, the statistical evidence on the impacts of interest rates on bank profitability has not been extensively explored. The focus of my chapter lies in exploring the differential impacts of changes in interest rates on bank profit when interest rates are low and high. In the literature, only Claessens et al. (2018) has developed a robust method to disentangle the effect of a low and high interest rate with a panel of banks for a large sample of countries. In their study, they perform a dynamic econometric analysis where NIM of banks is regressed annually for each country on the level of the three-month sovereign rate, and the yield curve, controlling for lagged value of the bank's NIM, other bank-level variables, economic conditions, and it also includes bank fixed effect

and a time fixed effect. The analysis is conducted by splitting bank-years observations into low- vs. high-rate environments through the use of dummy variables. They classify a country's low-rate environment if its average 3-month bond yield for that year is less than or equal to 1.25 percent and assign a dummy equal to 1 and 0 otherwise to find the varying effects of changes in interest rates on bank NIMs. To my knowledge, no country specific study has attempted to classify the differential impacts of changes in interest rates on bank profitability. As a contribution, I split the sample into low and high-interest rate environments by giving relative focus on different interest rate environments to see which environment describes stronger association between interest rates and bank profitability in US.

In this context, I use the approach of Seo & Shin (2016) and Seo et al. (2019) which outlines a method to estimate dynamic panel with threshold effects and endogeneity. In the literature, the panel threshold models were originally introduced by Hansen (1999) and have also been applied to applications on bank profitability and business cycles (Apergis, 2009), bank profit and economic growth (Ho & Saadaoui, 2022) and optimal bank size and profitability (Chang et al., 2011) etc. The model developed by Hansen (1999) is static in nature and his fixed effect estimator assumes strict exogeneity of the covariates to obtain a consistent estimator. But the requirement of strong exogeneity assumption can be overly restrictive in practice. To address this limitation, Seo & Shin (2016) extend the model to the dynamic panel model with a potentially endogenous threshold variable. Their model incorporates lagged dependent variables and endogenous covariates which allows me to deal with the issue of endogeneity when investigating the association between bank profits and interest rates.

There is a strand of literature which investigates the important determinants of bank profitability and other factors which can affect bank performance using dynamic panel threshold

approach by Seo & Shin (2016). For instance, Bolarinwa et al. (2021) explore potential threshold effects in the nexus between nonperforming loans and bank profitability in Nigeria's banking sector using the dynamic panel threshold approach by Seo & Shin (2016). Their findings suggest that commercial banks can achieve optimal profitability at a lower threshold level of non-performing loans, highlighting important policy implications: reducing non-performing loans to this level would not harm, and may even enhance, bank profitability. Molla (2022) investigates whether R&D expenditure exhibits a threshold effect on the performance of listed banks in Bangladesh over the 2011 to 2019 period. To contribute to the bank performance literature, their study is the first to use dynamic panel with threshold effects and endogeneity to access bank data to analyze the threshold effect of R&D expenditure on bank performance.

Built on the principles of GMM, Seo & Shin's (2016) approach accounts for potential endogeneity which is difficult to eliminate in the nexus between interest rates and bank profitability. Simultaneously, this methodology can help to find the appropriate threshold level of interest rates to divide the sample into low and high-interest rate environments to find its differential effects on bank profitability.

Studies highlight the changes in short-term interest rates, particularly those dictated by the Federal Reserve's monetary policy, have a profound effect on bank NIM, which reflects the difference between interest income and interest expenses relative to interest-bearing assets. However, the impact varies across bank types. Community banks, typically smaller institutions with a stronger reliance on traditional deposit funding, tend to exhibit greater sensitivity to changes in short-term interest rates than larger, non-community banks. This is because community banks have fewer sources of non-interest income, meaning they are more dependent on the spread between deposit rates and loan rates (Morris & Regehr, 2014; Rezende et al., 2015). Several studies

have indicated the presence of threshold effects, meaning that the relationship between interest rates and NIM is not linear. At low levels of interest rates, particularly in the post-crisis environment, banks experience margin compression as deposit costs hit a floor, while loan yields continue to decline. Community banks are more vulnerable to these thresholds due to their narrower product offerings and higher reliance on deposit funding (Lightfoot & Gonitzke, 2021). For instance, when interest rates are very low, community banks' NIMs suffer more compared to larger banks, which can offset the decline with other income sources. However, when interest rates rise above certain thresholds, the profitability of community banks improves more rapidly as they can pass on rate increases to loans quicker than to deposits (FDIC, 2021; Kansas City Fed, 2022).

Non-community banks, or larger banks, tend to have more diversified portfolios and multiple streams of income, such as trading revenue or fee-based services, which make them less sensitive to fluctuations in short-term interest rates. They tend to have more advanced hedging strategies to alleviate interest rate risk. According to Rezende et al. (2015), non-community banks, often rely on non-deposit liabilities due to their larger size and funding strategies respond differently to rate changes than deposit-based funding which makes them less sensitive to short-term interest rate fluctuations. In contrast, community banks rely heavily on net interest income from traditional lending and deposit-taking activities. This reliance makes them more vulnerable to changes in short-term interest rates, particularly during tightening cycles where loan demand might decrease (Morris & Regehr, 2014; Rezende et al., 2015).

3.3 Data and Descriptive Statistics

For this study, balance sheet data is collected on all U.S. commercial banks insured by the Federal Deposit Insurance Corporation from 2001Q1 to 2021Q1, stemming from the quarterly Call Reports which is the standard in the literature. This allows me to track the evolution of changes in the interest rate environment by investigating different periods such as before and after the financial crisis and also the new interest rate environment which covers the time before and after the COVID-19 pandemic. Several filters are applied on the balance sheet data. Following Chang & Talley (2017) banks with negative total shareholders' equity should be deleted from the sample because they indicate financial distress or insolvency, which can bias the analysis and violate model assumptions because their financial situation is very different from normal banks. Moreover, those observations are dropped in which assets are zero which likely means that the bank is either not operating anymore or there was a mistake in reporting the data (Claessens et al., 2018). Following Bikker & Vervliet (2018), I omit extreme values and undefined ratios from the sample through winsorizing to get a balanced sample which contains 330,480 bank-year observations, which consists of 4080 individual banks. In addition, it is worth mentioning that a balanced panel dataset is a mandatory requirement to employ Seo and Shin's (2016) dynamic panel threshold model.

The macroeconomic quarterly data on gross domestic product (GDP) growth, consumer price index (CPI) inflation, long-term interest rates and short-term interest rates are acquired from FRED database maintained by the Federal Reserve Bank of St. Louis. Quarterly averages are used for all variables.

3.3.1 Dependent Variable

The main objective of a bank is to maximize its profitability. In the literature, there are several variables used as an indicator of bank performance such as net interest income, net profit, return on assets, and return on equity. According to Lall (2014), one of the most important measures to estimate the profitability of a bank is the net interest margin (NIM). Therefore, in this paper NIM is used as a measure of bank profitability and represents the difference between interest income and interest expense as a ratio of total assets (Bikker & Vervliet, 2018; Claessens et al., 2018; Hwang, 2020).⁴¹ The interest income must be higher than the interest expense in order to earn a positive profit.

3.3.2 Independent Variables

3.3.2.1 Bank Specific Variables

In line with previous studies on the effects of bank determinants on profitability of banks, this paper uses various bank specific factors to examine the effect of interest rates on banks' NIM (for example Demirgüç-Kunt & Huizinga, 1999; Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011; Bikker & Vervliet, 2018; Genay & Podjasek, 2014; Borio & Gambacorta, 2017).

- **Bank Size** is estimated by the logarithm of total assets (Bikker & Vervliet, 2018; Chang & Talley, 2017). However, there is no clear consensus in the literature on the effect of bank size on profitability.

⁴¹ Interest income is constructed as the sum of income from loans, lease financing, balances due from depository institutions, securities, federal funds sold, and other interest income, as reported in the Call Reports. Interest expense is constructed as the sum of interest paid on deposits (transaction and non-transaction accounts), federal funds purchased, and other interest expenses, as reported in the Call Reports.

- **Capitalization** indicates the overall financial health of a bank and is calculated as the ratio of total equity capital over total assets. Bank capital is expected to positively affect banks' NIM (Athanasoglou et al., 2008; Bikker & Vervliet, 2018; Borio & Gambacorta, 2017; Genay & Podjasek, 2014).
- **Lending** is approximated as the ratio of total loans over total assets (Bikker & Vervliet, 2018; Dietrich & Wanzenried, 2011). A higher volume of loans tends to increase net interest income and thus affects bank profitability positively, but the associated rise in credit risk may potentially erode profits.
- **Diversification** is measured by the ratio of total non-interest income over total income which represents the dependence of a bank on standard financial intermediation activities in which it generates non-interest income via fee and commission (Bikker & Vervliet, 2018). The association between non-interest income and bank profitability is negative as the more a bank relies on non-interest income, the lower the bank profitability is (Dietrich & Wanzenried, 2011).
- **Deposit to liability** ratio is measured as deposits expressed as a percentage of total liabilities (Claessens et al., 2018). A positive coefficient is expected, as deposits act as a cost-effective funding source.

3.3.3 Macroeconomic Variables

Macroeconomic conditions play a very important role in determining the association between bank profitability and interest rates. For example, most of the studies use macroeconomic indicators, such as inflation, rate of GDP growth, and exchange rate which reflect the state of economic conditions. In this study real GDP growth rate is used to control for the effect of business

cycle on bank profitability. An increase in real GDP is expected to contribute positively to NIM (Bikker & Vervliet, 2018; Claessens et al., 2018).

Following Bikker & Vervliet (2018), my study also takes the 3-month money market rate as short-term interest rate. Lower interest rates are expected to harm the bank's NIM. The relationship between the short-term interest rate and bank profitability is thus anticipated to have a positive coefficient (Claessens et al., 2018). The slope of the yield curve is the difference between 10-year bond rate and 3-month money market rate. A reduction in the short-term interest rate or a flattening of the yield curve tends to reduce bank profitability (Genay & Podjasek, 2014). As an economic indicator, inflation also captures dynamics of the business cycle. Empirical evidence generally suggests a positive inflation impact on profits. Demirgüç-Kunt & Huizinga (1999) study points to a positive relationship between inflation and NIM, implying that elevated inflation boosts income generated through bank float.

Figure 3.1: Movements of Short and Long-term Interest Rates

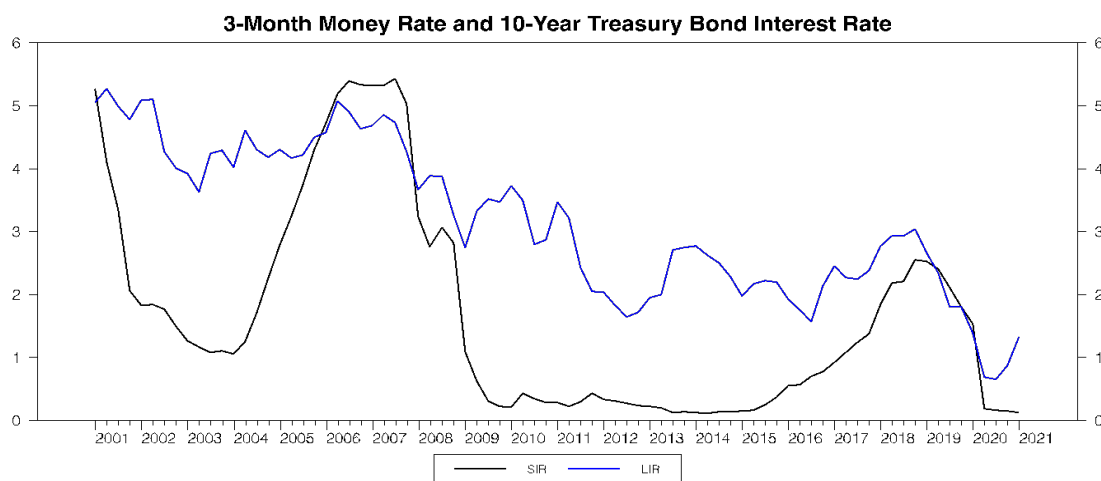


Figure. Patten of 3-Month Money Rate and 10-Year Treasury Bond Interest Rate from 2001q1 to 2021q1

Figure 3.1 shows significant movements of both short- and long-term interest rates from 2001Q1 to 2021Q1. We can see key fluctuations such as the steep interest rate decline during the

2008 financial crisis and the COVID-19 pandemic as well as the prolonged low-rate environment. It also represents a strong connection between short term interest rates and the Federal Reserve policy as short-term interest rates show immediate changes in response to economic conditions. However, long term interest rates move more gradually as they are influenced by market expectations. Taken together, short- and long-term interest rates reflect significant monetary policy shift and economic cycles over the two decades.

Figure 3.2: Movements of the Fed Funds Rate and Average Net Interest Margin

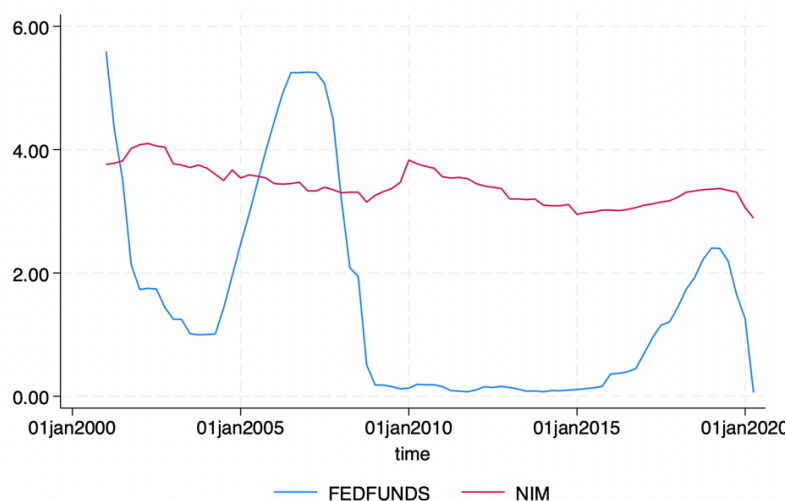


Figure 3.2 shows relationship between the fed funds rate and NIM. Short-term interest rates tend to mirror the fed funds rate more closely and exhibit greater volatility. As a result, these yields are expected to be the most sensitive to policy-induced interest rates hikes.

Table 3.1: Bank Sample Used for Panel Threshold Model

	No. of observations	No. of Individual banks	Average number of years under observations
Balanced Sample	330,480	4080	20.25 years (81 quarters)
Unbalanced Sample	549,584	6785	20.25 years (81 quarters)

Table 3.1 shows the number of bank-year observations of balanced and unbalanced sample. One of the critical considerations when applying the dynamic panel threshold model proposed by

Seo & Shin (2016) is the use of a balanced sample. A balanced panel dataset has observations for all cross-sectional units (e.g., banks) across all time periods. This consistency ensures that the estimation process utilizes the full dataset effectively, leading to more reliable and consistent parameter estimates. The dynamic panel threshold model estimates the threshold value that differentiates the regimes (e.g., high and low-interest rate environments). A balanced sample ensures that each unit contributes equally to the estimation of this threshold, improving the accuracy and robustness of the threshold estimate.

In Table 3.2, the bank level income variable, NIM, shows substantial variation. NIM exhibits a standard deviation of 1.2 percent which is not very high relative to its mean 2.2 percent. The mean of capitalization is 11.34 percent with a standard deviation of 4.20 percent. Banks maintaining a higher capital to asset ratios are safer and more likely to sustain profitability amid economic downturns. Furthermore, reduced risk enhances a bank's creditworthiness and lowers its funding cost. Moreover, a higher equity-to-assets ratio reduces dependence on external funding, thereby enhancing bank profitability. The mean value of diversification is 0.14 which indicates that 14 percent of total income comes from non-interest income sources like fees and trading, while the remaining 86 percent of income relies on traditional interest income. This implies that most banks are heavily dependent on interest-based revenue which increases their sensitivity to interest rate changes. The mean value of 0.61 for bank lending indicates that, on average, 61% of total assets are allocated to loans, highlighting a strong emphasis on lending. The significant variability of lending shows that some banks are being highly loan-focused while others maintain more diversified asset allocations. The deposit over liabilities ratio varies across observations considerably. This indicates that the data includes both banks engaged in conventional financial intermediations with higher deposit to liabilities ratios, as well as those that are increasingly

involved in capital market activities which tend to rely more heavily on wholesale funding sources. The mean yield curve is 1.49 percent with a standard deviation of 1.18 percent. The average real GDP growth is 0.46 percent, with a minimum value of -8.94 percent and a maximum value of 7.55 percent. There are substantial differences in the short-term interest rate during the study period. It can be seen in Table 3.2 that the minimum short-term interest rate is 0.11 percent, while the maximum rate is 5.42 percent. The average long-term interest rate for the period is 3.15 percent which is higher than the average short-term interest rate. However, the standard deviation of long-term interest rate is comparatively lower than the short-term interest rate standard deviation.

Table 3.2: Descriptive Statistics (Balanced Sample):

Variables	Mean	Std. Dev.	Min	Max	N
Bank-Level Data:					
NIM	0.022	0.012	-0.029	0.627	330,480
Size	12.077	1.4143	6.8330	21.8888	330,480
Capitalization	0.1134	0.0420	0.0626	0.3738	330,480
Diversification	0.1385	0.1194	0.0053	0.8370	330,480
Lending	0.6176	0.1647	0.0553	0.9021	330,480
Deposit to liability	0.9323	0.0961	0.3151	0.9992	330,480
Macro-Level Data					
Real GDP Growth	0.46	1.44	-8.94	7.55	330,480
Yield Curve	1.49	1.18	-0.76	3.51	330,480
Short-term Rate	1.67	1.64	0.11	5.42	330,480
Long term Rate	3.15	1.20	0.65	5.27	330,480
Inflation	2.06	1.18	-1.62	5.30	330,480

3.3.4 Mergers and Acquisitions

The estimation is based on a balanced sample. Attrition bias arises in the unbalanced sample as some bank-year observations are missing due to mergers and acquisitions or bankruptcy. It could be argued that, for example, only the most profitable and resilient banks survive bankruptcy and are thus present over the entire sample period. Thus, the balanced sample may give

a biased impression, as it includes only the most financially sound banks. However, controlling for attrition bias is difficult and likely negligible due to the large sample size.

3.3.5 Outliers

A winsor function is used to substitute the outliers' values with more acceptable values. To finalize the process, the detailed statistic of the variable is checked to see the distribution of the observations. If the histogram indicated that extreme values were significantly distant from the majority of the observations (i.e. abnormally extending the tail), the winsor function was applied to effectively replace these values. Moreover, using the summary statistics I was able to identify those values below the xth percentile and above the yth percentile that appeared to exhibit skewness. The winsor function mitigates the influence of outliers by replacing values below and above specified percentiles with the nearest values at those boundaries.

Table 3.3: Winsor Characteristics

Variable	Winsor Features
Capitalization	Winsor for 0.5, 99.5
Diversification	Winsor for 0.5, 99.5
Deposit to Liability	Winsor for 0.5, 99.5

In Table 3.3, to reduce the influence of extreme outliers some of the bank-level variables including capitalization, diversification and deposit to liability ratio were winsorized at the 0.5th and 99.5th percentiles. Specifically, the values below the 0.5th percentile and above the 99.5th percentile were replaced with the corresponding cutoff values. This transformation preserves all observations while minimizing the effect of extreme values on the analysis.

3.3.6 Correlation Analysis

Gujarati (2010) suggests that when the correlation coefficients between the explanatory variables are less than 0.80, the issue of multicollinearity is unlikely to pose significant concerns for regression analysis. The results of pairwise correlation matrix coefficients in Table 3.4 indicates no significant threat of multicollinearity among variables. The highest correlation coefficient is 40 percent between deposit to liabilities ratio and diversification. As all pairwise correlations remain below the conventional threshold (0.80), multicollinearity is not a major concern.

Table 3.4: Correlation Matrix

	NIM	Size	Capitalization	Diversification	Lending	Deposit to Liabilities	Real GDP Growth Rate	Yield Curve	Short-term Interest rate	Inflation
NIM	1.0000									
Size	-0.0347	1.0000								
Capitalization	-0.0209	-0.1644	1.0000							
Diversification	-0.0631	0.1891	0.2941	1.0000						
Lending	0.2035	0.1998	-0.3373	-0.2444	1.0000					
Deposit to Liabilities	0.0721	-0.2318	-0.2551	-0.4082	0.0989	1.0000				
Real GDP Growth Rate	0.0910	-0.0029	-0.0041	0.0204	-0.0248	0.0155	1.0000			
Yield Curve	-0.0234	-0.0573	-0.0348	0.0300	-0.0720	0.0049	0.0900	1.0000		
Short-term Interest Rate	0.0489	-0.1073	-0.0144	-0.1121	0.0754	-0.0748	-0.0335	-0.6848	1.0000	
Inflation	0.0636	-0.0761	-0.0185	-0.0587	0.0193	-0.0447	0.0945	-0.3380	0.5661	1.0000

3.3.7 Stationarity

The asymptotic theory underlying panel threshold models requires that all regressors be stationary. Hence, a key assumption of dynamic panel threshold methodology is that all variables in equation 3 are I(0) stationary in level. Baltagi (2005) recommends that panel-based unit root

tests offer higher power relative to individual time-series unit root tests, particularly in panels with a large cross-sectional dimension and moderate time span. In Table 3.5 all panel unit root tests demonstrate a common null hypothesis that all panel units (e.g., banks) contain unit roots however, their alternative hypotheses and underlying assumptions differ. The Levin, Lin, and Chu (LLC) test assumes a common stationarity process across all panels under the alternative and a rejection of the null hypothesis in the Levin-Lin-Chu test suggests the absence of unit roots.

Table 3.5: Panel Unit root test result

Variable	Im–Pesaran–Shin (IPS)	Levin-Lin-Chu (LLC)	Harris–Tzavalis (HT)
Net Interest Margin	-5.7154 p-value = 0.000	-210.00 p-value = 0.000	0.3575 p-value = 0.000
Size	-2.5039 p-value = 0.000	-9.3447 p-value = 0.000	0.8953 p-value = 0.000
Capitalization	-3.0855 p-value = 0.000	-28.5906 p-value = 0.000	0.8128 p-value = 0.000
Diversification	-3.3501 p-value = 0.000	-22.7041 p-value = 0.000	0.7525 p-value = 0.000
Lending	-2.8868 p-value = 0.000	-12.5588 p-value = 0.000	0.8297 p-value = 0.000
Deposit to Liability	-3.7815 p-value = 0.000	-57.9658 p-value = 0.000	0.7471 p-value = 0.000
Real GDP growth rate	-10.8815 p-value = 0.000	-370.00 p-value = 0.000	-0.2127 p-value = 0.000
Yield Curve	-2.0527 p-value = 0.000	-5.1892 p-value = 0.000	0.9120 p-value = 0.000
Short-term Interest Rate	-2.0445 p-value = 0.000	11.0985 p-value = 0.000	0.9399 p-value = 0.000
Inflation	-3.3950 p-value = 0.000	-200.00 p-value = 0.000	0.7506 p-value = 0.000

The Im, Pesaran, and Shin (IPS) test, by contrast, allows for heterogeneous stationarity which means only a subset of cross-sections needs to be stationary. The Harris and Tzavalis (HT) test, which is particularly suited for balanced panels with large N and small to moderate T, assumes the entire panel is stationary under the alternative. These tests are complementary and provide

robust insights into the stationarity properties of the data when used together.⁴² Table 3.5 shows that all variables are stationary at their level, as the test results consistently reject the presence of unit roots.

3.4 Methodology

This study is motivated by the possibility that the interest rate will impact bank NIM in a nonlinear way for the optimal level of short-term interest rate. To test for potential nonlinearity in this relationship, I employ the first-differenced generalized method of moments estimation (FD-GMM Estimator) of the dynamic panel threshold model developed by Seo & Shin (2016) and Seo et al. (2019) which extends Hansen's panel threshold regression model (1999). The panel threshold model with the fixed effect estimates the threshold value by minimizing the sum of residual squares and evaluates the significance of the identified threshold value while controlling for unobserved, time-invariant characteristics of each bank that could otherwise bias the relationship between short-term interest rate and NIM. The core idea involves selecting a particular variable as the threshold variable and partitioning the regression model into intervals based on the estimated threshold value. Due to potential endogeneity between the short-term interest rate and NIM, the traditional static threshold model proposed by Hansen (1999) is not appropriate for this study (Abdul Karim et al., 2022). Moreover, Hansen's (1999) model assumes the covariates to be strictly exogenous to ensure the consistency of the estimator, making it unsuitable for this research. Thus, it is for my research to use the dynamic panel model with an endogenous threshold variable.

⁴² <https://www.stata.com/manuals13/xtxtunitroot.pdf>

I consider the following dynamic panel threshold regression model:

$$y_{it} = (1, x'_{it})\alpha_1 I(q_{it} \leq \gamma) + (1, x'_{it})\alpha_2 I(q_{it} > \gamma) + \varepsilon_{it} \quad (1)$$

$$\{i=1, \dots, N; t=1, \dots, T\}$$

where N and T denote the cross sections and time dimensions of the panel, respectively, i represents the bank, t indexes time; $\varepsilon_{it} = \mu_i + \theta_{it}$ is the error components, where μ_i captures unobserved individual fixed effect and θ_{it} represents a zero mean idiosyncratic random disturbance. Specifically, θ_{it} is assumed to be martingale difference sequence, $E(\theta_{it}|F_{t-1}) = 0$, where F_t is a natural filtration at time t .

Following Seo and Shin (2016), the application of the differenced GMM estimation is further explained as follows. Using a 1-dimensional vector of instrument variables, $(z_0^{it}, \dots, z_{iT}^{it})$ was selected from both lagged and exogenous variables, where $2 < t_0 \leq T$.⁴³ This method follows a structured approach using differenced GMM to address endogeneity while removing fixed effects. Moreover, selecting instruments from lagged endogenous variables starting from lag $t-2$ and relevant exogenous variables provides a robust set of instruments for estimation (see Bolarinwa et al., 2021). I consider the following dynamic regression model:

$$\begin{aligned} NIM_{it} = & a_1 NIM_{it-1} + \beta_1 STinterest_t + \beta_2 Size_{it} + \beta_3 Cap_{it} + \beta_4 Divers_{it} + \beta_5 Lend_{it} + \\ & \beta_6 Dept_{it} + \beta_7 GDP_t + \beta_8 YC_t + \beta_9 CPI_t \end{aligned} \quad (2)$$

⁴³ $t_0 = 3$ denotes the initial time period from which valid moment conditions can be constructed after first differencing, reflecting the use of lagged instruments starting from $t-2$.

I then extend (2) into the dynamic panel data framework with threshold effects.

$$\begin{aligned}
NIM_{it} = & (a_1 NIM_{it-1} + \beta_{1,1} STinterest_t + \beta_{2,1} Size_{it} + \beta_{3,1} Cap_{it} + \beta_{4,1} Divers_{it} + \beta_{5,1} Lend_{it} \\
& + \beta_{6,1} Dept_{it} + \beta_{7,1} GDP_t + \beta_{8,1} YC_t + \beta_{9,1} CPI_t) I(STinterest_t \leq \gamma) \\
& + (a_2 NIM_{it-1} + \beta_{1,2} STinterest_t + \beta_{2,2} Size_{it} + \beta_{3,2} Cap_{it} + \beta_{4,2} Divers_{it} + \beta_{5,2} Lend_{it} \\
& + \beta_{6,2} Dept_{it} + \beta_{7,2} GDP_t + \beta_{8,2} YC_t + \beta_{9,2} CPI_t) I(STinterest_t > \gamma) \\
& + \mu_i + \theta_{it}
\end{aligned} \tag{3}$$

where $I(\cdot)$ is an indicator function, $STinterest_t$ is the threshold variable and γ is the threshold parameter which splits the sample into regimes. The regime-specific coefficients on each regressor are denoted by $\beta_{k,1}$ and $\beta_{k,2}$, where the second index indicates the regime. I estimate (3) by the proposed FD-GMM, which allows for both (contemporaneous) regressors and the threshold (transition) variable to be endogenous. This procedure addresses both fixed effects and endogeneity concerns, in contrast to the threshold model introduced by Hansen (1999), which was developed for static panel settings and assumes exogeneity of both the regressors and the threshold variable. Unlike Hansen's static framework, my model of interest is dynamic (persistence in the behavior of NIM advises including lagged value as explanatory variable) and it allows for potentially endogenous regressors due to reverse causality and simultaneity issues. Moreover, existing studies (e.g., Ampudia & Van den Heuvel, 2022; Borio et al., 2017) employed lagged values of short-term interest rate and bank level variables (e.g. bank size, bank capital, diversification, lending) as instruments to address potential endogeneity in both the regressors and the threshold variable.

For the purpose of estimating this model, I use the Stata routine `xthenreg` developed by Seo et al. (2019). I instrumented the endogenous variables – the lagged dependent variable, threshold

variable (short-term interest rate) and bank level variables (bank size, bank capital, diversification, deposit to liabilities, lending) under consideration – using internal instruments, i.e. the lags of these variables and contemporaneous exogenous variables (GDP growth, CPI, yield curve). As the choice of instruments is consistent with the existing literature, I select lagged values of endogenous variables. This FD-GMM estimator incorporates a grid search procedure, where different candidate threshold values are evaluated and the value that minimizes the GMM objective function is selected as the best fit. After determining the threshold estimate, the sample is divided into two regimes: one below and one regime above the threshold and the model is estimated for each regime accordingly.

3.4.1 Testing for Threshold Effects

The dynamic panel model also employs a bootstrap algorithm to examine the existence of a threshold effect in the model, capturing potential nonlinearities. This test is conducted under following hypothesis:

Null Hypothesis: $\beta_1 = \beta_2$

Alternative Hypothesis: $\beta_1 \neq \beta_2$

The null hypothesis of the linearity test is that the difference between the coefficients in the two regimes is zero. Rejection of the null hypothesis of no threshold implies evidence in favor of a threshold effect. In simple terms, a p-value below 0.05 indicates the presence of a threshold variable in the estimation at the 5% significance level.

3.4.2 Significance of the Methodology

The choice of this method is justified with a few main arguments. Firstly, to estimate the link between banks' NIM and interest rate, one must take into account the initial level of banks' NIM, otherwise, a bias of specifications may rise. Endogeneity may pose a challenge (unbiased estimators, false conclusions) in the estimation of bank profitability models based on linear regressions on panel data since the initial bank profitability in these models is endogenous by construction. The estimation of a dynamic equation using the Generalized Method of Moments (GMM) helps to solve this problem (Caselli et al., 1996) Thus, using a dynamic model is appropriate to address the relation between banks' NIM and short-term interest rate.

Secondly, heterogeneity, a key concern in large panels, is not sufficiently handled in a fixed dynamic panel threshold method. Since the fixed dynamic panel threshold model assumes a homogeneous threshold effect across entities, which limits its ability to account for individual variability in large panels. Seo and Shin's dynamic panel threshold model uses GMM to manage endogeneity and incorporate dynamic relationships, providing more accurate estimates in the presence of heterogeneity.

Thirdly, non-linearity plays a central role in the dynamics of interest rate and banks' NIM. Empirical studies suggest that one promising way to model non-linearity is through regime switching frameworks. These models provide an economic rationale for the observed non-linearity. Following Ampudia & Van den Heuvel (2022) and Borio et al. (2017), it is indicated that the relationship between NIM and interest rates follows an inverted U-shaped non-linear pattern. The non-linear relationship between the short-term interest rate and NIMs provides meaningful proof that the impact of the short-term interest rate on NIMs plays a crucial role in determining the "reversal effect" between the short-term interest rate and banks' NIM. This means that while NIM

might initially increase (decrease) with rising (falling) interest rates, beyond a certain threshold, further increases in interest rates could lead to a decrease in NIM.

Fourthly, this method allows the use of an endogenous threshold. One approach to examine threshold effects is the non-dynamic panel threshold model developed by Hansen (1999) in which the threshold variable and all regressors are treated as exogenous. Therefore, this model is not suitable to analyze the threshold effects between banks' NIM and interest rate due to the endogeneity issue. To address this issue, Kremer et al. (2013) propose an estimation method for panel data that accounts for endogeneity bias. Their framework extends Hansen's (1999) non-dynamic panel threshold model and Caner & Hansen's (2004) instrumental variable estimation in a threshold effects model. But Kremer's model requires the threshold to be exogenous. Therefore, my work employs the dynamic panel threshold approach developed by Seo & Shin (2016) which is flexible to use an endogenous threshold variable. This estimation strategy is based on the principle of generalized method of moments (GMM) developed by Arellano & Bond (1991); Arellano & Bover (1995); Holtz-Eakin et al. (1988) and Blundell & Bond (1998) to produce robust and efficient estimates despite the presence of dynamic endogeneity and heteroscedasticity inherent in the relationship.

Literature often employs quadratic models to capture the non-linear relationship between short-term interest rate and banks' NIM. This method is subject to a significant limitation. The inclusion of the squared term of short-term interest rate in the quadratic model for determining the threshold effect of short-term interest rate in the relationship between short term interest rate and bank's NIM brings a prior limitation that the effect of short-term interest rate on bank profitability varies monotonously and symmetrically in response to the level of short-term interest rate. However, reaching a specific level of short-term interest rate may be required for short-term

interest rate to have any effect on banks' NIM. This is accounted for in a threshold model but overlooked in a quadratic specification. Accordingly, this study applies a regression framework based on the concept of threshold effect to examine how short-term interest rate affects banks' NIM.

3.5 Main Results and Discussion

The results obtained from the dynamic panel threshold model for all US. commercial banks using the short-term interest rate as the threshold variable are reported in Table 3.6. As can be seen, the bootstrap p-value of the linearity test confirms the main hypothesis that the effect of short-term interest rate on NIM depends on the level of short-term interest rate. Hence, the observations of the sample can be divided into two regimes. The lower regime contains the observations below the estimated short-term interest rate threshold. The upper regime contains the observations above the estimated threshold.

The results yield a positive effect of the short-term interest rate on NIM with an effect size of 0.0011 in the low-interest rate environment. That is, a decrease (increase) in the short-term rate of 1 percentage point implies a decrease (increase) in NIM of 0.11 percentage points which indicates when the endogenous short-term interest rate is below 2.82% threshold, NIM decrease on average by 11 basis points. This result is in line with that of Alessandri & Nelson (2015), Demirgüç-Kunt & Huizinga (1999) and Genay & Podjasek (2014). Based on these results, it can be inferred that in a low-interest rate environment, a fall in short-term interest rate leads to a decline in the NIM, which is the bank's main source of profitability. This is consistent with the assumption that banks struggle to earn profits from their conventional lending and funding operations when interest rates are low. Banks are hesitant to quickly lower deposit rates as interest rates decline but

continue to transmit the lower rates to existing and new loans based on contractual repricing and competition induced by borrowers who have other financial choices.

Table 3.6: Dynamic Panel Threshold Estimation: All U.S. Commercial Banks

This table presents the results of Dynamic Panel Threshold Approach derived by Seo and Shin (2016). The dependent variable is the net interest margin which represents the difference between interest income and interest expense as a ratio of total assets. Estimation sample is 2001Q1 – 2021Q1. Linearity test is the bootstrap test of linearity where the null hypothesis is the no threshold effects.

Variables	Net Interest Margin	
	Low-Interest Rate Regime	High-Interest Rate Regime
Lag of NIM	-0.1021*** (0.00002)	0.0816*** (0.0004)
Short-term Interest Rate	0.0011*** (0.0006)	-0.0048*** (0.0008)
Capitalization	0.1415*** (0.00004)	-0.2014*** (0.00008)
Bank Size	-0.0044*** (0.00012)	-0.0051*** (0.0002)
Lending	-0.0334*** (0.0008)	-0.0094*** (0.0001)
Deposit to liability	0.0404*** (0.0002)	-0.0801*** (0.0004)
Diversification	-0.0788*** (0.0002)	-0.0577*** (0.0003)
Real GDP growth rate	0.00002*** (0.00008)	-0.00024*** (0.0004)
Yield Curve	0.000006*** (0.00002)	-0.0079*** (0.0009)
Inflation	-0.00017*** (0.00004)	0.00043*** (0.0003)
Constant	0.1860*** (0.00006)	
Threshold	2.817	
Bootstrap (p-value)	0.000	
N	4080	
No. of moment conditions	32864	

Note: Standard errors are in parentheses. ***p<0.01, **p<0.05, and *p<0.1. N refers to the number of banks. The stata command “xthenreg” is used to estimate the results. The value of bootstrapping, grid points, and trim rate are set as 100, 50, and 0.4, respectively.

Source: Author, from stata.

Consequently, decline in interest rates may lead to imperfect pass-through of policy rates to various market rates, which may potentially hinder the effectiveness of monetary policy and result in compressed NIMs. Therefore, a decline in short-term interest rate contributes to lower

NIM, as interest expense falls less than interest income in the low interest-rate environment. In the high-interest rate environment, which is above the threshold, the results show a negative effect of the short-term rate on NIMs with an effect size of 0.0048. That is, a decrease (increase) in the short-term interest rate of 1 percentage point implies an increase (decrease) in NIMs of 48 basis points which indicates when the short-term rate is above 2.82% threshold, NIMs increases on average by 48 basis points when interest rate decreases by 1 percentage point. This inflection point indicates a threshold beyond which the costs of lower interest rates are outweighed by the associated benefits, leading to margin expansion. The findings are consistent with Busch & Memmel (2017) which underscores the importance of understanding the non-linear dynamics between interest rates and bank profitability, highlighting that beyond specific thresholds, lower rates can favorably impact NIM. This indicates that above the interest rate threshold, in the high-interest rate environment a decrease in interest rate increases NIM due to a mismatch between falling funding costs and slower asset yield adjustments. As interest rates falls, banks are forced to offer lower deposit rates to customers, decreasing funding costs significantly. However, many interest-earning assets, such as fixed-rate loans or securities, do not reprice as quickly, enhancing the ability to offset funding costs (FDIC, 2021). These results also provide evidence claimed by Ennis et al. (2016) that in the case of traditional banking based on maturity transformation – characterized by interest sensitive liabilities and relatively interest insensitive assets – falling interest rates can cause an increase, rather than a decrease, in NIM. Additionally, falling borrowing costs increase loan demand, allowing opportunities to expand higher-yield lending (Borio et al., 2017).

In terms of other variables, I observe that larger banks are linked to lower NIM in both interest rate environments which is consistent with Demirgüç-Kunt & Huizinga (1999) and

Dietrich & Wanzenried (2011). Larger banks often rely more on non-interest income sources (e.g., fees, commissions, and trading income) than on traditional lending and deposit activities. Moreover, large banks benefit from economies of scale by operating efficiently with lower NIM which can improve their performance while reducing their risk exposure. This finding aligns with the conclusions of Nasserinia et al. (2015) for German banks and Horváth (2009) for the Czech banking sector. Moving to bank capital, better capitalized banks tend to exhibit higher net interest margins, consistent with the findings of Demirgüç-Kunt & Huizinga (1999) which is the case in low-interest rate environment. High-interest rate environment in contrast shows a negative coefficient on bank capital which implies that higher capitalization reduces NIM. Banks with higher capital levels often invest conservatively in low-risk, lower-yield assets, which become less profitable as rates rise. The result aligns with Carb-Valverde et al. (2009), who analyzed the European banking sector. Also, in the low-interest rate environment a positive coefficient on the ratio of deposits to liabilities indicates that banks with a higher proportion of their liabilities composed of deposits tend to have higher NIMs due to providing cost advantage. A negative coefficient on the deposit-to-liabilities ratio implies that higher reliance on deposits relative to other liabilities does not support NIM in a high-interest rate environment. Core deposits, often a low-cost funding source in normal conditions, reprice upward in competitive environments, increasing funding costs disproportionately. The inability to offset rising deposit costs with higher asset yields contributes to NIM compression. Additionally, banks that depend more heavily on non-interest income i.e., are more diversified, display lower net interest margins which is supported by related studies of Demirgüç-Kunt & Huizinga (1999) and Dietrich & Wanzenried (2011). A negative coefficient on diversification suggests that banks with more diversified income sources see lower NIM in both interest rate environments. A larger loan portfolio generates most

of the net interest income which determines profit positively (Dietrich & Wanzenried, 2011) but my findings show it affects riskiness through the quality of the loan portfolio. A negative coefficient on lending indicates that higher lending volumes are associated with lower NIM in both regimes. Rising rates may increase borrower default risk, leading to higher provisions for loan losses. Loan demand may also decline, as higher borrowing costs deter potential borrowers, reducing the ability to generate interest income.

In the low-interest rate environment, the coefficient on GDP growth is positive and significant and validates the interpretation that NIMs are low in low-interest rate environments as a result of prevailing economic weakness and constrained lending opportunities (Dietrich & Wanzenried, 2011). A negative coefficient on real GDP growth indicates that economic expansion does not necessarily support NIM in the high-interest rate environment. While growth often boosts loan demand, in the high-interest rate environment, the increased cost of borrowing may offset this benefit. I also find the slope of the yield curve has a positive effect on NIM, consistent with the expectation that banks engage in maturity transformation. While I continue to include yield curve in the regressions, I will place less emphasis on the results on it for this paper like Claessens et al. (2018) approach. A negative coefficient on the yield curve implies that a flattening or inversion of the curve harms NIM in the high-interest rate environment. Banks typically borrow short-term (deposits) and lend long-term (loans). A flatter yield curve reduces the spread between short-term funding costs and long-term asset yields. A negative relationship between inflation and NIM suggests that higher inflation leads to a decrease in banks' NIM. Studies such as Demirgüç-Kunt & Huizinga (1999) and Borio et al. (2017) highlight the negative impact of inflation on bank profitability due to rising funding costs and asset-liability mismatches. A positive coefficient on inflation suggests that inflationary environments support NIM. Inflation drives increase in loan

yields, benefiting banks with variable-rate assets. However, this positive impact may not be sufficient to counteract the overall negative effects of high rates on NIM.

Next, I focus on the distinctive impacts of the short-term interest rate on NIM in different interest rates highlighting the inherent structural and strategic distinctions between community and non-community banks in the US economy.

In Table 3.7, the relationship between the short-term interest rate and NIM for community banks demonstrates clear regime-dependent behavior, with a positive coefficient of short-term interest rate in low-interest rate environment and a negative coefficient of short-term interest rate in high-interest rate environment. This shows that community banks, which are deeply reliant on traditional banking activities such as lending and deposit-taking, experience varying impacts on their NIM across different interest rate environments. In a low-interest rate environment, a fall in short-term interest rate decreases NIM because loan yields, especially from floating-rate loans, adjust downwards faster than deposit rates, which tends to remain sticky (Hinton & Polson, 2021; FDIC, 2021). That is, a decrease (increase) in the short-term interest rate of 1 percentage point implies a decrease (increase) in NIM of 0.04 percentage points which indicates when the endogenous threshold of short-term interest rate is below 2.55%, NIM decreases on average by 4 basis points. This dynamic underscore the importance of asset sensitivity in low-interest rate environment, where the structure of a bank's loan portfolio—such as the proportion of floating-rate loans—plays a critical role in determining the extent of NIM deterioration (Hinton & Polson, 2021; FDIC, 2021).

However, in the high-interest rate environment, as the short-term interest rate surpasses a critical threshold of 2.55%, the relationship reverses as deposit and funding costs drop due to the downward repricing of core deposits, which make up a significant portion of their liabilities, while

loan demand strengthens, and asset yields fail to decrease at the same pace because of limited asset repricing flexibility (Kansas City Fed, 2022).

Table 3.7: Dynamic Panel Threshold Estimation: Community Banks

This table presents the results of Dynamic Panel Threshold Approach derived by Seo and Shin (2016) for community banks. The dependent variable is the net interest margin which represents the difference between interest income and interest expense as a ratio of total assets. Estimation sample is 2001Q1 – 2021Q1. Linearity test is the bootstrap test of linearity where the null hypothesis is the no threshold effects.

Variables	Community Banks' Net Interest Margin	
	Low-Interest Rate Regime	High-Interest Rate Regime
Lag of NIM	-0.1000*** (0.00006)	0.2753*** (0.0002)
Short-term Interest Rate	0.0004*** (0.00008)	-0.0031*** (0.0001)
Capitalization	-0.3206*** (0.0001)	0.2851*** (0.0002)
Bank Size	-0.0123*** (0.00003)	0.0078*** (0.00006)
Lending	0.0724*** (0.0002)	0.0346*** (0.0003)
Deposit to liability	0.0337*** (0.0004)	0.0170*** (0.0005)
Diversification	0.0305*** (0.0002)	-0.1049*** (0.0005)
Real GDP growth rate	0.00002*** (0.00001)	-0.00063*** (0.0004)
Yield Curve	0.00012*** (0.00001)	-0.0015*** (0.0001)
Inflation	0.00017*** (0.00001)	-0.00027*** (0.0002)
Constant	-0.1391*** (0.00009)	
Threshold	2.5520	
Bootstrap (p-value)	0.000	
N	3319	
No. of moment conditions	32864	

Note: Standard errors are in parentheses. ***p<0.01, **p<0.05, and *p<0.1. N refers to the number of banks. The stata command “xthenreg” is used to estimate the results. The value of bootstrapping, grid points, and trim rate are set as 100, 50, and 0.4, respectively.

Source: Author, from stata.

The threshold, therefore, marks a tipping point which highlights the nonlinear and asymmetric impact of short-term interest rate changes on community banks' NIM (Borio et al., 2017). This suggests that a decrease (increase) in the short-term rate of 1 percentage point implies

an increase (decrease) in NIM of 0.31 percentage points which indicates when the endogenous threshold short-term rate is above 2.55%, NIM increases on average by 31 basis points. Thus, when interest rates fall from a high level, community banks typically benefit from mismatch between declining funding costs faster than asset yields which temporarily improves NIM.

Moving to control variables, a negative coefficient on bank capital in the low-interest rate environment suggests that higher capital levels are associated with lower NIM. This could reflect that community banks with higher capital ratios may not fully utilize their capacity to lend or invest in high-yield assets, especially in a low-yield environment. So, in the low-interest rate environment higher capital levels may reduce NIM due to inefficient asset allocation.⁴⁴ A positive coefficient on bank capital in the high-interest rate environment suggests that well-capitalized banks are better able to sustain or enhance NIM. This could reflect higher capital levels provide a cushion against rising funding costs, enabling banks to maintain competitive lending rates. Rising rates compress NIM but higher capital levels can mitigate this effect by enhancing resilience to rising costs (Kansas City Fed, 2022). In the low-interest rate environment, community banks larger in size benefit more from falling interest rates because they rely more on core deposit which are less sensitive to interest rate changes, and they also engage in relationship-based lending which allows them to sustain higher loan yields even as interest rate falls (White, 2021). In the high-interest rate environment, instead of smaller community banks larger banks are better equipped to sustain NIM because of their ability to reprice assets, diversify funding, and leverage economies of scale in managing rising costs (Kansas City Fed, 2022).

⁴⁴ <https://www.communitybankingconnections.org/articles/2013/Q1/Effective-Asset-Liability-Management?>

A larger loan portfolio generates most of the net interest income which determines profit positively (Dietrich & Wanzenried, 2011). My results show that in low-interest rate environment, lending activity also declines alongside NIM, as reduced loan demand in a low-rate environment further limits banks' ability to generate interest income (White, 2021). In high-interest rate environment, lending activity positively contributes to NIM, as effective loan repricing or diversification into higher-yield loan segments, such as commercial or real estate lending, helps offset some of the pressures from rising funding costs. While lending can provide a buffer, the overall benefit is limited by the rapid escalation of deposit rates in high-interest rate environment, which compresses NIM (Kansas City Fed, 2022). Furthermore, deposit-to-liabilities ratio has a positive relationship with banks' NIM. In low-interest rate environment, a decline in the deposit-to-liabilities ratio increases funding costs and reduces stability in funding which compresses NIM of community banks. However, in high-interest rate environment, banks with more deposits relative to total liabilities benefit from lower funding costs and greater flexibility to allocate resources to interest-earning assets which increases NIM (White, 2021). Additionally, banks with greater reliance on non-interest income, have smaller NIM which is supported by related studies of Demirgüç-Kunt & Huizinga (1999) and Dietrich & Wanzenried (2011). In low-interest rate environment, diversification positively impacts NIM by reducing dependence on interest income and adding stable non-interest income streams. This enhances the ability of community banks to benefit from rising short-term interest rates, as their overall income structure becomes more resilient to low loan yields and stable deposit costs. However, diversification negatively impacts NIM as rising funding costs compress NIM, and non-interest income streams fail to offset the decline.

In the low-interest rate environment, the coefficient on GDP growth is positive and significant and support the interpretation that NIM increase in low-interest rate environment because of economic growth (Dietrich & Wanzenried, 2011). However, in high-interest rate environment a negative coefficient on real GDP growth indicates that economic expansion does not necessarily support NIM. While growth often boosts loan demand, in high-interest rate environment, the increased cost of borrowing may offset this benefit. Moreover, inflation contributes to higher NIM as it often raises nominal loan yields faster than deposit rates, especially in low-interest rate environment where deposit costs are sticky. Inflation in high-interest rate environment negatively impacts NIM because it raises funding costs (e.g., deposit rates) more sharply than loan yields. Additionally, inflationary pressures can increase credit risk by straining borrowers' repayment ability, further compressing NIM. I also find a positive effect on NIM related to the slope of the yield curve which is to be expected since a large role of banks is maturity transformation. A negative coefficient on the yield curve implies that a flattening or inversion of the curve harms NIM in the high-interest rate environment.

Table 3.8 shows the positive coefficient on NIM for U.S. non-community banks in both low and high-interest rate environment which reflects their structural advantages, income diversification, and balance sheet management. Non-community banks benefit from significant non-interest income sources, such as fees and trading revenue, which buffer NIM against the pressures of changing interest rates (Borio et al., 2017). In the low-interest rate environment, falling short-term interest rate positively impacts NIM due to decreased loan demand while their larger funding base helps keep deposit costs stable reducing NIM. That is, a decrease (increase) in the short-term interest rate of 1 percentage point implies a decrease (increase) in NIM of 0.007

percentage points which indicates when the endogenous threshold of short-term interest rate is below 2.76%, NIM decreases on average by 0.7 basis points.

Table 3.8: Dynamic Panel Threshold Estimation: Non-Community Banks

This table presents the results of Dynamic Panel Threshold Approach derived by Seo and Shin (2016) for non-community banks. The dependent variable is the net interest margin which represents the difference between interest income and interest expense as a ratio of total assets. Estimation sample is 2001Q1 – 2021Q1. Linearity test is the bootstrap test of linearity where the null hypothesis is the no threshold effects.

Variables	Non-Community Banks' Net Interest Margin	
	Low-Interest Rate Regime	High-Interest Rate Regime
Lag of NIM	-0.0678*** (0.0004)	0.1467*** (0.0028)
Short-term Interest Rate	0.00007*** (0.00002)	0.0006*** (0.0001)
Capitalization	0.1651*** (0.004)	-0.4480*** (0.0198)
Bank Size	0.0037*** (0.0001)	0.0031*** (0.0005)
Lending	-0.0265*** (0.001)	-0.1333*** (0.0043)
Deposit to liability	-0.0099*** (0.0007)	0.0112*** (0.0044)
Diversification	-0.0108*** (0.0009)	0.0174*** (0.0033)
Real GDP growth rate	-0.00010*** (0.00003)	-0.0016*** (0.00009)
Yield Curve	0.0015*** (0.0001)	-0.0013*** (0.0001)
Inflation	0.0005*** (0.00007)	0.0004*** (0.0005)
Constant	0.0651*** (0.0109)	
Threshold	2.764	
Bootstrap (p-value)	0.000	
N	147	
No. of moment conditions	32864	

Note: Standard errors are in parentheses. ***p<0.01, **p<0.05, and *p<0.1. N refers to the number of banks. The stata command “xthenreg” is used to estimate the results. The value of bootstrapping, grid points, and trim rate are set as 100, 50, and 0.4, respectively.

Source: Author, from stata.

In a high-interest rate environment, when short-term interest rate falls non-community banks experience a decline in NIM as the drop in loan yields tends to outpace the decline in funding costs. Although these banks possess advantage such as diversified income stream which supports

overall profitability but does not directly stabilize net interest margins which are strictly tied to the spread between interest income and interest expenses. This suggests that a decrease (increase) in the short-term rate of 1 percentage point implies a decrease (increase) in NIM of 0.06 percentage points which indicates when the endogenous threshold short-term rate is above 2.76%, NIM decrease on average by 6 basis points. Their consistent positive NIM performance across interest rate environments underscores their resilience to interest rate fluctuations, unlike more interest rate-sensitive community banks.

Analyzing the control variables, better-capitalized banks tend to achieve higher NIM in the low-interest rate environment, as their stability and lending capacity allow them to benefit from margin expansion (Demirgüç-Kunt & Huizinga, 1999). However, in the high-interest rate environments, larger non-community banks face margin compression as rising funding costs and reduced loan demand outweigh the advantages of capital, diminishing its competitive benefits. In both low and high-interest rate environment, non-community banks which are larger in size as compared to community banks are better equipped to sustain NIM because of their ability to reprice assets, diversify funding, and leverage economies of scale in managing rising costs (Kansas City Fed, 2022). A negative coefficient on lending indicates that higher lending volumes are associated with lower NIM in both interest rate environments. Rising interest rates may increase borrower default risk, leading to higher provisions for loan losses. Loan demand may also decline, as higher borrowing costs deter potential borrowers, reducing the ability to generate interest income through lending. Furthermore, the regime-dependent role of deposits to liability ratio in shaping NIM dynamics for non-community banks shows that deposits may be less advantageous in the low-interest rate environment, their stability becomes a strategic asset in the high-interest rate environment. In the low-interest rate environment, non-community banks' reliance on non-

interest income sources may negatively impact NIM as these revenue streams reduce the relative contribution of interest-based earnings. This diversification dilutes the sensitivity of NIM to interest rate changes (Hinton & Polson, 2021; FDIC, 2021). However, in the high-interest rate environment, income diversification becomes beneficial and contributes positively to NIM for non-community banks. Non-community banks' ability to rely on non-interest income provides a buffer against

The negative GDP growth coefficient implies that GDP growth amplifies the decline in NIM when short-term interest rate falls in low-interest rate environment through increased competition, tighter loan spreads, and sticky funding costs that fail to offset reduced loan yields. In high-interest rate environment, during the period of economic growth banks compete aggressively for borrowers which drives down interest rate on loans which reduces banks' NIM. Moreover, in the low-interest rate environment, both falling interest rate and flattening of yield curve reduces NIM. However, in the high-interest rate environment, while rising interest rates continue to benefit NIM the negative yield curve coefficient reflects challenges from a flattening yield curve.

When I compare the findings across the three tables, which represent all commercial banks, community banks, and non-community banks, clear differences emerge in how short-term interest rate affects NIM across bank types and interest rate regimes which shows the unique structures and business approaches of these bank groups. For all commercial banks (Table 3.6), the threshold effect demonstrates that while rising short-term interest rate improve NIM in the low-interest rate environment initially, further increase starts to compress NIM once the threshold of 2.82% is surpassed which is likely due to weaker loan repricing capacity and rising funding cost. A comparable trend is evident in the case of community banks (Table 3.7) though with a slightly

lower threshold of 2.55%, indicating they are more sensitive to rate increases and reach the tipping point sooner which likely due to their reliance on traditional deposit funding and limited diversification. In contrast, non-community banks (Table 3.8) show a threshold of 2.76%, but the short-term interest rate coefficient remains positive in both regimes, implying these banks are better positioned to benefit from rising rates even in high-interest rate environment, possibly due to greater income diversification and more flexible funding sources. These differences highlight how bank structure and business models shape the impact of interest rate changes on profitability.

3.6 Conclusion

My study examines the nonlinear effects of interest rates on NIM for US commercial banks across low- and high-interest rate environment, using a dynamic panel threshold model to distinguish the impacts of rate changes in different environments. Having established a statistically, financially and economically significant endogenous threshold of short-term interest rate as one of the contributions to the literature, my findings show that there is a relationship between short term interest rate and banks' NIM. Particularly, the threshold value of short-term interest rate is 2.82% respectively, where the low-interest rate environment is indicated by a quarter in which the level of interest rate is below the threshold 2.82% while high-interest rate environment occurs when the interest rate exceeds this threshold. My results show that in the low-interest rate environment, the bank's NIM decreases (increases) when short term interest rate decreases (increases). This indicates when interest rates fall in a low-interest rate environment it adversely affects banks' NIM by lower the bank profitability. This is because loan yields, especially for floating-rate loans, tend to adjust downwards faster than deposit rates, resulting in NIM reduction (FDIC, 2021). However, in the high-interest rate environment, this relationship reverses and NIM increases when short-term interest rate decreases due to falling funding costs and strong loan

demand. Above the threshold in the high-interest rate environment, the relationship reverses and turns negative and banks face NIM expansion (Ampudia & Van den Heuvel, 2022). We can also interpret it conversely that when interest rates rise further in a high- interest rate environment, banks' NIM decrease. This occurs because funding costs, including deposit and wholesale funding rates, increase more rapidly than loan yields, compressing margins. Additionally, high interest rates can reduce loan demand and increase credit risk, further dampening profits (Borio et al., 2017).

Moreover, my study is the initial attempt to explore nexus between interest rate and NIM by using the method of dynamic panel threshold model of Seo & Shin (2016) which addresses problem of endogeneity which arises when lagged NIM or interest rates, are correlated with the error term. Moreover, this method also captures a non-linear relationship between interest rate and bank NIM which provides a meaningful proof that there exists a regime-dependent non-linear relationship between interest rates and banks' NIM (Ampudia & Van den Heuvel, 2022; Borio et al., 2017). Moreover, unlike other regime switching estimation techniques (Hansen, 1999; Kremer et al., 2013), the model of Seo & Shin (2016) is flexible to use an endogenous threshold variable which ensures unbiased estimation. Hence, this method provides a robust framework to analyze how interest rates influence NIM across interest rate environments, identifying critical interest rate threshold that inform both academic research and policy decisions

Another contribution of this study is also the initial investigation into the threshold effect of interest rate on bank NIM for community and non-community banks, offering new insights into their performance across different interest rate environments. The divergence in interest rate effects on NIM in both environments reflects the fundamental differences in the structure and strategy of these segments of the US banking industry. My results show the threshold value is 2.55% for

community banks and in the low-interest rate environment NIM decreases with a fall in short-term interest rate because loan yield adjust downwards faster than deposit rates, which tends to remain sticky (Hinton & Polson, 2021; FDIC, 2021). However, above 2.55% threshold, deposit and funding costs drop due to the downward repricing of core deposits, which make up a significant portion of their liabilities, while loan demand strengthens, and asset yields fail to decrease at the same pace because of limited asset repricing flexibility (Kansas City Fed, 2022). Non-community banks on the other hand maintain NIM in both environments due to their diversified income sources, flexible funding strategies, and the ability to reprice loans more effectively. My results show that in the low-interest rate environment, a fall in the short-term interest rate adversely effects NIM when the endogenous threshold is below 2.76%. However, in the high-interest rate environment when interest rate is above 2.76% threshold, if short-term interest rate starts to decline, non-community banks also experience a decline in NIM as the drop in loan yields tends to outpace the decline in funding costs. Although these banks possess advantage such as diversified income stream which supports overall profitability but does not directly stabilize net interest margins.

These results have far-reaching implications, for bank managers, but also for central bankers as policymakers must carefully consider the tipping point to balance financial stability and bank performance. Understanding this threshold is essential for helping banks stay resilient, diversify their income sources, and manage risks. However, a crucial limitation would be the sensitivity of interest rate threshold to data and model specifications which can affect reliability of results.

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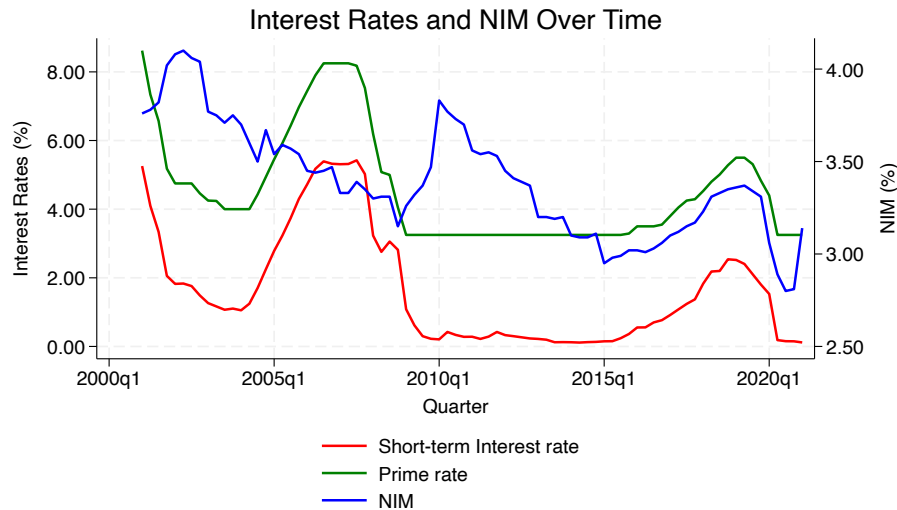
Federal Reserve Bank of St. Louis.

Appendix C

Appendix Table 3.2: Sources of Model Variables

Variable	Definition	Source	Code
Net Interest Margin (NIM)	Difference between interest income and interest expense, Divided by total assets	Call Reports	(RIAD4107-RIAD4073)/ RCON2170
Size	Logarithm of total assets	Call Reports	Log (RCON2170)
Capitalization	Total equity capital over total assets	Call Reports	RCON3210/RCON2170
Diversification	Total non-interest income over total income	Call Reports	RIAD4079/ (RIAD4107 + RIAD4079)
Lending	Total loans over total assets	Call Reports	(RCON2122 +RCON2123)/ RCON2170
Deposit to Liabilities	Total deposits over total liabilities	Call Reports	RCON2200/RCON2948
Real GDP growth	Average yearly GDP growth rate	FRED	
Inflation	CPI inflation	FRED	
Short term Interest rate	3-month money market rate	FRED	
Long Term Interest rate	10-year government bond	FRED	

Appendix Figure 3.1: Relationship between Short-term Interest Rate, Prime lending rate and US. Commercial Bank Net Interest Margin



Appendix figure 3.1 shows the evolution of short-term interest rates, the prime lending rate and bank’s NIM for US. Commercial banks from 2001Q1 to 2021Q1. The short-term interest rate captures the stance of monetary policy and moves closely with economic cycle. The prime rate, which tracks the policy rate with a constant spread, shows a similar pattern. This graph helps visualize the asymmetric, regime-dependent effects of interest rates captured by the threshold model. When interest rates fall to very low levels-as in early 2000’s post-2008, and during COVID-19, NIM declines which is consistent with the findings that rate cuts in the low-interest rate environment compress NIMs because deposits rates cannot fall further while loan yields decline. In contrast, modest increases in rates from these low levels are associated with gradual improvements in NIM, supporting the findings. However, when interest rates rise into higher territory, such as during the 2004-2007 tightening cycle or the 2016-2019 normalization period, NIM does not increase proportionally and often flattens or declines. This aligns with the threshold results that, in the high interest-rate environment, further rate increases tighten funding conditions, causing NIM to contract.

Conclusion

This dissertation has examined the role of U.S. commercial banks in the transmission of monetary policy, with a particular focus on non-performing loans, deposits, and bank profitability. While each essay addressed a distinct aspect of banking, together they highlight how commercial banks function as critical intermediaries whose balance sheets both reflect and shape macroeconomics dynamics.

The first essay focused on non-performing loans, shedding light on how economics disruptions and monetary easing during the pandemic affected loan quality of community banks in the U.S. banking sector. The analysis revealed that loan performance is highly sensitive to crisis conditions and that policy tried mitigating credit risk pressure.

The second essay investigated the behavior of deposits during the COVID-19 crisis and the Federal Reserve's unprecedented monetary interventions. The findings underscore the importance of the conventional and unconventional monetary policy actions as an amplification mechanism of the monetary policy, with deposit flows responding asymmetrically across banks of different sizes.

The third essay examined the nonlinear relationship between interest rates and bank profitability, measured through net interest margin. Employing the dynamic panel threshold model of Seo and Shin (2016), the study identified regime-dependent effects, showing that profitability dynamics differ substantially across low and high-interest rate environments. This contribution fills a gap in the U.S. literature, where a specific a specific interest rate threshold is identified. The results have important implications for the conduct of monetary policy in an era of interest rate volatility.

Taken together, the three essays illustrates that U.S. commercial banks are active participants in shaping financial and economic outcomes. The findings suggest that banking system health is integral not only to financial stability but also to the effective ness of monetary transmission.

Future research can extend these insights by examining how digital banking innovations and shifts in global financial conditions reshape the role of U.S. banks in policy transmission. In addition, future work could also undertake cross-country analyses to better understand how institutional differences shape the lending, deposits, and profitability responses documented here. Ultimately, this dissertation highlights that a deeper understanding of commercial banks behavior is vital for designing policies that strengthen financial system resilience and enhance the effectiveness of monetary policy in both normal and crisis times.