8-16-2024

Four Essays on Banking, Bank Management, and Bank Lending

Jiarui Guo

University of South Carolina

FOUR ESSAYS ON BANKING, BANK MANAGEMENT, AND BANK LENDING

by

Jiarui Guo

Bachelor of Commerce
The University of Alberta, 2016

Master of Science
Johns Hopkins University, 2017

Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Business Administration

The Darla Moore School of Business

University of South Carolina

2024

Accepted by:

Allen N. Berger, Major Professor

Omrane Guedhami, Committee Member

John Hackney, Committee Member

Ai He, Committee Member

Ann Vail, Dean of the Graduate School

Dedication

This dissertation is dedicated to my parents and grandparents. Their support makes me reach beyond my potential. Also, thanks to H. Montague (Monty) Osteen, Jr. for his generous support.

ABSTRACT

This abstract synthesizes findings from four studies examining the liquidity creation, bank-borrower relationships, corporate capital structure, and managerial impact on firm performance, particularly within the context of banking and financial crises, including the COVID-19 pandemic.

The research first identifies the dual shocks of the pandemic—disease and policy-driven (government shutdowns)—on bank liquidity creation. I find that these shocks prompted banks to reallocate liquidity creation from assets (decreasing loans) to liabilities (increasing liquid deposits), which reduced profits and heightened risks.

In exploring bank-borrower relationships, the study highlights the role of banks in utilizing soft private information, such as the moral character of firm management, to bolster credit provision, especially to bank-dependent firms lacking solid, quality hard information. This relationship lending technology is crucial for firms that otherwise might not qualify for traditional credit avenues.

Further, a comprehensive analysis involving nearly 60,000 firms across 110 countries over 17 years investigates the effects of bank debt on corporate value. Results reveal that high-intensity use of bank debt (90% or more of total corporate debt) is strongly correlated with enhanced firm value. This correlation is more pronounced in credit-constrained firms, such as smaller companies and those in developing countries. The study differentiates the impacts of term loans and credit lines on short-term and long-term firm

performance, respectively, suggesting nuanced capital structure strategies during financial crises like COVID-19.

Lastly, the role of managerial actions in firm performance is examined through the lens of exogenous shocks inducing managerial turnover. By focusing on the banking industry and utilizing detailed government-mandated data, findings underscore that managerial quality significantly boosts firm performance by improving asset turnover and product quality, which are reflected in both market valuations and accounting measures.

Together, these studies provide insightful implications for banking practices, debt management strategies, and managerial approaches in navigating through financial crises and enhancing firm performance. These insights are particularly relevant for policy formulation and understanding the intricate relationships within financial systems during turbulent times.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. NOT ALL BANK LIQUIDITY IS CREATED EQUAL: EVIDENCE FROM EXOGENOUS SHOCKS DURING COVID

Abstract

Banks play a central role in creating liquidity for the economy and financial system. The pandemic introduced two exogenous shocks to the demand of bank liquidity: the pandemic shock from disease, and the policy shock from government shutdown mandates. Using unique bank liquidity creation data, I find that both shocks reduced overall bank liquidity creation, however, they created a shift of liquidity creation from the asset side to liability side of bank balance sheet: cash and securities increased while bank loans decreased on the asset side, and liquid deposits surged on the liability side. This shift reduced profits and increased risks. However, unlike the pandemic shock, the policy shock caused less immediate damage but facilitated stronger recovery but did not work well with expansionary monetary policy.

1.1. Introduction

Banks have central roles in the real economy and financial markets, and one of the roles is creating liquidity for their customers. As a result, firms can have loans to expand their businesses, consumers can have deposits to facilitate their spending and savings, and non-bank financial market participants can carry on their trading and price discovery functions. Banks create liquidity by using all parts of their portfolios, assets, liabilities, and off-balance sheet (OBS) items, but mainly through loans, deposits, and loan commitments. However, a key question remains open: Does liquidity created using different combinations of these instruments have the same implications for banks? I address this question in the context of the COVID-19 crisis.

The COVID-19 crisis emerged as a unique disruption to bank liquidity creation. In stark contrast to earlier economic and financial downturns, banks remained robust during the onset of the COVID-19 pandemic, while their clients faltered. Hence, this situation offers a clear lens to examine the demand-side impact on bank liquidity. Also, the unpredictability of the crisis makes it exogenous to the economy and financial system. In particular, the crisis presents a paradox: on the one hand, anticipated reductions in economic activities could diminish liquidity demand—evidenced by restaurants curtailing borrowing due to decreased dine-in customers. On the other hand, the liquidity needs could surge as businesses and households confront dwindling incomes, possibly pushing them to seek more loans or lean on readily available deposits.

Two main shocks were introduced to the economy during the crisis: the direct effects of the pandemic and the collateral damage of public health policy responses, termed "pandemic" and "policy" shocks respectively. This paper offers a comprehensive empirical exploration of the implications of these two shocks on bank liquidity creation. I find that the two shocks together caused a quantity decline and a compositional shift in bank liquidity creation. Specifically, while total bank liquidity creation decreased, more liquidity was created on the liability side of bank balance sheets mainly through liquid deposits, and much less liquidity was created on the asset side of bank balance sheets due to increase in cash and securities and decreases in all bank loans except for the Paycheck Protection Program (PPP) loans. This increase in PPP loans is expected because these loans were designated to support businesses during COVID and were made under substantially lenient standards. Moreover, perhaps in response to potential increases in withdrawals from the surging liquid deposits, cash and securities also increased. As a result of the shift between the asset-side and liability-side liquidity creation, bank profitability fell, and risks elevated. In addition, I observe that the pandemic shock has stronger effects during the crisis time, but the policy shock produces stronger recovery.

I construct the bank liquidity creation measures following Berger and Bouwman (2009). The liquidity creation measures are net quantities, inclusive of portfolio items that create, destroy, or little affect customer liquidity. Positive, negative, and zero weights are assigned to these items, respectively. This approach involves classifying all balance sheet items into three categories: liquid, semi-liquid, and illiquid. Then, weights are assigned to each of the categories (more details are provided in Appendix 1). A notable example is cash and securities. Cash and securities are liquid, and banks take liquidity away from the economy by holding them on the balance sheet. Another example is transaction and savings deposits. Banks create liquidity by issuing transaction and savings deposits since they are more liquid than cash because transactions using these two types of accounts are easier.

I construct my main dependent variables and control variables using Call Reports which contain detailed financial information on U.S. commercial banks. The pandemic shock and the policy shock are measured by new COVID-19 cases and government policy responses in the states where a bank operates respectively. New COVID case data is from

Economic Tracker[1] (Chetty, Friedman, Hendren, and Stepner, 2023), and the government policy responses are measured by the stringency index from OXCGRT[2] (Hale, Angrist, Goldszmidt, Kira, Petherick, Phillips, Webster, Goldszmidt, Hallas, Majumdar, and Tatlow, 2021). My sample period spans from 2019:Q1 to 2022:Q4. There are 5,099 banks in my sample.

In the first part of my analysis, I conduct ordinary least square (OLS) analysis to examine the effects of the pandemic shock and the policy shock on total bank liquidity creation as well as each of the components. I find that total bank liquidity creation decreased with the two shocks, however, the shocks produced differential effects on the asset-side and OBS-side activities from the liability-side activities: the asset-side and OBS-side liquidity creation decreased with the shocks while the liability-side liquidity creation increased with them. These differential effects are driven by the compositional changes in liquidity creation: due to changes in the economic outlook, the liquidity created for development and expansion, such as bank loans, shrinked whereas the liquidity created to meet short-term needs, such as transaction and savings deposits, surged. The increases in liquid deposits forced banks to build up their cash and securities so that they could meet potential amplified withdrawal requests, which further reduced asset-side liquidity creation. In this process, the effects of the disease are always larger than the effects of the policies. Overall, the demand shock leads to a significant shift between asset-side and liability-side liquidity creation.

[1] https://tracktherecovery.org/

[2] https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker

I employ an instrumental variable approach in the second step to investigate the implications of the shift on bank performance. Specifically, I use the pandemic shock and the policy shock as my instruments to isolate the relevant variations in the difference between liability-side and asset-side liquidity creation. Then, I examine the relations between the predicted difference and bank profitability and risk measures. My results suggest that the predicted difference leads to a significant reduction in banks' profitability and a considerable rise in the risks, which is consistent with the drop in bank capital ratio.

In additional analysis, expansionary monetary policy has differential influences over the effects of the two shocks. While expansionary monetary policy weakly exacerbates the effect of the pandemic shock, it strongly and significantly alleviates the effect of the policy shock on bank liquidity creation. This result provides evidence that the monetary policy was well-coordinated with administrative policies during the COVID crisis and successfully prevented more adverse consequences from happening. Moreover, I find that the shift is wider for big banks because they can hoard relatively more cash and securities and make fewer loans while making slightly more liquid deposits. Lastly, my crisis-aftermath analysis shows that the effects of the demand shocks were overturned from 2021 to 2022, the recovery period. Notably, the economic significance of the pandemic shock is substantially larger than the policy shock during the crisis, but they become equal-sized in the recovery period. This suggests that although the shutdown policy produced adverse effects to the economy during COVID, it preserved the resilience of the economy which spurned stronger resurgence once the crisis passed.

Lastly, I examine the influence of monetary policies on the effects of the two shocks. I find that expansionary monetary policies in general encourage liquidity creation by supporting lending. In particular, these policies alleviate the effect of the disease while their effect is reduced by the public health policies. It suggests that coordinating different types of policies during crisis time can be important. Efforts should be made in avoiding policies impeding each other.

My paper contributes to the bank liquidity creation literature and the COVID-19 crisis literature. The importance of bank liquidity creation was recognized in banking theory several decades ago (e.g., Bryant, 1980; Diamond and Dybvig 1983; Holmstrom and Tirole, 1998; Kashyap, Rajan, and Stein, 2002). It was not empirically examined until Berger and Bouwman (2009). Since then, a large amount of empirical papers have been devoted to investigating drivers of bank liquidity creation. For example, Berger and Bouwman (2009) find bank size and bank capital ratio play an important role. Jiang, Levine, and Lin (2018) suggest regulation-induced competition reduces bank liquidity creation. A number of papers show a variety of government policies may or may not have significant influences on bank liquidity creation. For example, Berger, Bouwman, Kick, and Schaeck (2016) find that government intervention can significantly influence bank liquidity creation whereas capital support cannot. Berger and Bouwman (2017) show that monetary policy has very limited effect on bank liquidity creation. All the studies mentioned above focus on the supply-side effect. My paper studies the demand effect of bank liquidity creation and conducts a thorough investigation on all major components of bank liquidity creation.

My paper is the first to provide a comprehensive investigation into the effects of the COVID-19 crisis on bank liquidity creation. There is a huge body of literature on the COVID effects on banks, and existing papers have three main focuses: bank lending, bank profitability, and bank risk. For example, Acharya and Steffen (2020), and Li, Strahan, and Zhang (2020) document “dash for cash” where firms drew down their credit lines and raised their cash holdings. The literature finds that banks are tightening credit supply (e.g., Li, Strahan, and Zhang, 2020; Acharya, Engle, and Steffen, 2021; Greenwald, Krainer, and Paul, 2021; Kapan and Minoiu, 2021; Chodorow-Reich, Darmouni, Luck, and Plosser, 2022). My findings are consistent with their findings and further show similar results from much broader types of loans than these papers. In terms of bank profitability, studies concentrate on the effect of PPP loans. For example, Marsh and Sharma (2021) find that PPP participation negatively contributes to bank profitability whereas Berger, Karakaplan, and Roman (2022) find the opposite. My results contribute to the discussion by showing that the reason for the conflict between their findings may be that they do not take liquidity creation, especially shift, into account. With respect to bank risk, most of the literature focuses on the systemic risk contribution of banks. For example, Duan, El Ghoul, Guedhami, Li, and Li (2021) study systemic risks of banks around the world, and Borri and Di Giorgio (2022) cover banks in Europe. They all find that banks’ contributions to systemic risk increased during COVID. I contribute to the literature by studying the overall risk of individual banks. I show that the shift in liquidity creation caused by the pandemic shock and the policy shock reduces bank z-score significantly, suggesting that the overall bank risk increases.

The rest of this paper is organized as follows: Section 2 discusses data and the sample with an emphasis on the liquidity creation measure over time. Section 3 presents my main results. Section 4 presents the implication of changes in bank liquidity creation using an instrumental variable approach. Section 5 presents additional analysis. Section 6 concludes.

1.2. Data and sample

My data primarily comes from Call Reports, which contain detailed financial information on U.S. commercial banks. My key dependent variables are the liquidity creation measure and its components from Berger and Bouwman (2009). The liquidity creation data ends in 2016. I extend the data to 2022:Q4. My key independent variables pertain to the shocks from the COVID-19 crisis. Specifically, these independent variables are the pandemic shock and the policy shock. The pandemic shock is measured by quarterly new COVID-19 cases data from Economic Tracker (Chetty, Friedman, Hendren, and Stepner, 2023). I construct a bank's pandemic shock as the weighted sum of the bank's shock to COVID-19 cases in the states it operates. The weights are given by the number of branches of a bank in a state divided by the total number of branches, as outlined in equation (1). Similarly, I use the stringency index from OXCGRT (Hale, Angrist, Goldszmidt, Kira, Petherick, Phillips, Webster, Goldszmidt, Hallas, Majumdar, and Tatlow, 2021) to construct the policy shock. The stringency index reflects the extent and strictness of government policies regarding prohibiting social and economic activities. For instance, if a state imposes both business closure and school closure, it will have a high stringency index and, thus, a larger policy shock. The bank level policy shock is calculated in the same way as the pandemic shock following equation (1). The formula is as the following:

$$BankShock_{b,t} = \sum_{s \in all\ states} \frac{\#branch_{s,b,t-1}}{Total\ \#Branch_{b,t-1}} * LocalShock_{s,t} \tag{1}$$

where b indexes for banks, t indexes for time, and s indexes for states. COVID stands for local COVID-19 crisis shocks. The two shocks at the bank level reflect total shock of bank customers in the locality a bank operates to the pandemic and the responding policies.

In addition, I gather data on banks' Paycheck Protection Program lending from the Small Business Administration, monetary policy shocks (abbreviated as BRW, from Bu, Rogers, and Wu, 2019), and other macroeconomic control variables. These include the national gross domestic product growth rate and inflation, sourced from the Federal Reserve Bank of St. Louis, to complement my analysis. Since PPP loans significantly influence almost the entire balance sheets of banks, I do not directly control PPP loan volume in my regression to avoid statistical issues. Instead, I construct a PPP shock measure, which reflects the total volume of PPP loans made by other banks in the same localities where a bank extends PPP loans. The formula is the following:

$$PPPShock_{b,t} = \sum_{s \in all\ states} \sum_{i \in B_s, i \neq b} PPP\ Loans_{i,s,t} \tag{2}$$

where s stands for states, B is a set of all banks, b is the focal bank, and i indexes for each of other banks in state s. My sample period is 2019:Q1 to 2022:Q4. I include all U.S. banks with positive gross total assets (GTA)[3] throughout the sample period having at least one branch with non-zero deposits. I have a total of 5,099 banks and 78588 bank-year-quarter observations. Table 1.1 shows the summary statistics.

[3] Gross total assets, equals to the sum of total assets, the allowance for loan and lease losses, and the allocated transfer risk reserve.

1.2.1 Liquidity Creation from 2011Q1-2022Q4

Figure 1.1 illustrates the liquidity creation for banks since 2011. Until 2020, both total liquidity creation and liquidity creation on different sides of the bank balance sheet had been steadily increasing. Moreover, the composition of bank liquidity creation during this period remained stable. The increasing liability-side liquidity creation reflects the growth in deposits from U.S. households and corporations, while the rising asset-side liquidity creation demonstrates a strong demand for credit. Asset-side liquidity creation and liability-side liquidity creation have grown almost in parallel. Unlike the substantial volatility in off-balance-sheet-side (abbreviated as OBS) liquidity creation documented in Berger and Bouwman (2009), OBS liquidity creation remained relatively stable during this period, largely due to strengthened banking regulations following the 2008 crisis. This suggests that from 2011 to 2019, U.S. banks grew at a consistent pace.

However, with the onset of COVID-19 in 2020: Q1, bank liquidity creation underwent significant changes. The slope of total liquidity creation became notably steeper, driven by a massive increase in liability-side liquidity creation. Meanwhile, the asset-side liquidity creation did not grow at the same pace as its liability-side counterpart and instead began to decline, eventually turning negative.

1.3. Main Results

My main empirical model is as the following:

$$LC_{b,t} = \alpha_0 + \alpha_1 * PandemicShock_{b,t} + \alpha_2 * PolicyShock_{b,t} +$$

$$\alpha_3 * StimulusCheckShock_{b,t} + a_4 * PPPShock_{b,t} + \gamma * BankControls_{b,t-1} +$$

$$\delta * MacroControls_{t-1} + i_b + \epsilon_{b,t}, \quad (3)$$

where the dependent variables are liquidity creation measures and the components of bank liquidity creation. I control as many COVID-related policies as possible. One key policy concurrent shock is the stimulus checks. I include the total amount of stimulus checks paid in the state a bank operates in as the control. Also, PPP lending is another important policy—I use the sum of PPP loans made by other banks in each state a focal bank operates in as an exogenous control variable. *BankControls* is a vector of lagged control variables at the bank level, namely, total gross assets (GTA), capital ratio, return on assets (ROA), total expenses, and nonperforming loans. *MacroControls* is a vector of lagged macroeconomic control variables, including BRW monetary policy shocks, inflation rate, and GDP growth. I choose to control macroeconomic variables rather than time fixed effects because my main independent variables are common shocks to all banks in my sample. Therefore, the time fixed effects would absorb important variations in these shocks which I intend to explore. b stands for bank b, and t indexes for time. i_b is bank fixed effects.

Table 1.2 presents my primary findings. I assess the effects of the pandemic shock and the policy shock on total liquidity creation, asset-side liquidity creation, and liability-side liquidity creation across various specifications. Though the off-balance-sheet liquidity creation isn't the main focus of this paper, I include its results in column (10) for completeness. Overall, these two shocks exert robust, significant, and consistent impacts on total liquidity creation and liquidity creation from each segment of the banks' balance sheets. Moreover, the economic significance of the pandemic shock consistently exceeds that of the policy shock, given that the coefficients for the pandemic shock are substantially larger than those for the policy shock, while the standard deviations of the two shocks are strikingly similar. This implies that a one-standard deviation shift in the pandemic shock has a much greater impact than a corresponding shift in the policy shock. Specifically, results in columns (1)-(3) indicate that exposure to increased COVID new cases and stricter government COVID policies substantially diminishes bank total liquidity creation.

Subsequently, I dissect total liquidity creation into its components: asset-side, liability-side, and off-balance-sheet-side liquidity creation to pinpoint the factors contributing to the reduction in total liquidity creation. Columns (4)-(6) display the findings for asset-side liquidity creation. The coefficients for both the pandemic and policy shocks are negative and statistically significant. In terms of economic relevance, a one-standard deviation increase in the pandemic shock translates to a 24.7% (-0.361*0.0302/0.044) drop in asset-side liquidity creation on average, while a similar increase in the policy shock corresponds to a 3.3% (-0.076*0.0189/0.044) reduction. Even though 24.7% appears substantial, it's reasonable when considering that asset-side liquidity creation represents only a small fraction of overall bank liquidity creation.

Columns (7)-(9) elucidate the outcomes for liability-side liquidity creation. Both the pandemic and policy shock coefficients are positive and statistically significant. They also carry economic weight: a one-standard deviation uptick in the pandemic shock results in a 3.2% (0.283* 0.0302/0.267) increase in liability-side liquidity creation on average, while a similar uptick in the policy shock equates to a 0.3% (0.0420.0189/0.267) rise. Column (10) reveals that the associations between the shocks and off-balance-sheet liquidity creation are negative, albeit less pronounced and of lesser magnitude. My subsequent analysis will concentrate on the asset-side and liability-side liquidity creation.

I further decompose the asset-side and liability-side liquidity creation in Table 1.3. Columns (1)-(3) in Panel A of Table 1.3 show the relationships between the pandemic shock and the policy shock with major asset-side items. In particular, Columns (1) and (2) show the results for cash and securities, and federal funds sold, respectively. They are very liquid assets, and by holding them on the balance sheet, banks absorb rather than create liquidity from the rest of the economy. The positive and significant coefficients of the two shocks indicate that banks tend to hold more liquid assets when they are exposed to more COVID-19 new cases and more stringent government policies. Column (3) presents the result for total loans banks hold on their balance sheet. Making illiquid loans is an important way of liquidity creation, and the negative and significant coefficients of both shocks suggest that in general, banks reduce their lending in response to new COVID cases and strict government policies.

Columns (4)-(7) show the results for the main liability-side liquidity creation. Columns (4)-(5) present the results for transaction deposits and savings deposits. Transaction deposits and savings deposits are two main sources of liability-side liquidity creation as banks provide safe-keeping and transaction-facilitating services for these deposits, hence, making them very liquid. The positive and significant coefficients of both the pandemic shock and the policy shock suggest that depositors are depositing cash to liquid accounts.

There are three possible explanations: First, depositors convert their assets to cash or gain cash from government programs such as stimulus checks and deposit the cash to their accounts. If it is true, then I should observe the coefficients for the stimulus checks shock are positive and significant. However, the coefficients of the stimulus checks shock are negative, suggesting that depositors deposit less cash into transaction and savings accounts when they have stimulus checks to alleviate their liquidity demand. In addition, if this explanation is true, then time deposits should also increase. Second, banks with larger shocks to the pandemic and stringency policies raise deposit rates to attract more deposits. However, if this is true, then I should observe a large increase in time deposits rather than these two accounts because typically banks pay almost zero interest on these accounts and sometimes charge management fees on these accounts. Third, there is a compositional change in the structure of deposits—depositors shift their long-term deposits to these liquid accounts as they need more liquidity to deal with the pandemic and lockdowns. Corroborated with the result in Column (13), the third explanation seems to be most plausible because the effects of the pandemic shock and policy shock are negative and significant suggesting depositors move their illiquid deposits to more liquid accounts.

Lastly, the barely significant coefficients in Column (6) suggest that federal funds purchased by banks are not strongly affected, and the negative and significant coefficients of the pandemic shock and policy shock in Column (7) imply that banks' capital ratios deteriorated due to higher shock the COVID-19 and related government policies. Equity capital is negative liquidity creation because banks hold this resource from investors so they can absorb risks and losses. During the pandemic, banks may not be able to raise as much capital as they can during normal times. Moreover, the sickness and lockdowns might lead to more costs due to reduced labor supply and more losses in the loan portfolios, which erodes bank capital.

Panel B Table 1.3 presents the results for the main types of bank loans that have non-zero weights in the liquidity creation measure. The results show that when banks' customers are exposed to more new cases and more stringent policies, these banks decrease their lending in all types of loans except for PPP loans (Column (4)). These results are plausible because both the illness and mandatory closure/shutdown policies reduce the economic activities, thus, reduce demand for credits. This is consistent with the findings in the literature of the effects of the COVID crisis on the economy (Fairlie, 2020; Gourinchas, Kalemli-Ozcan, Penciakova, and Sander, 2020; Kim, Parker, and Schoar, 2020; Bloom, Fletcher, and Yeh, 2021; Fairlie and Fossen, 2021). Moreover, PPP loans are expected to be the exception because these loans are issued to help businesses to make paychecks and remain open, and the lending standard is much lower than regular bank loans.

1.4. The Implications of COVID Crisis on Bank Performance

The previous section presents the results for the impact of COVID crisis on liquidity creation activities. A natural question following is: what is the implications of the crisis to bank performance. Table 4 contains the results on how the crisis influences bank profitability and total risks.

1.5. Additional Analysis

I choose to focus on the balance sheet items that are directly relevant to bank businesses in the analysis below. I first conduct heterogeneity analysis on banks in different size groups and with different levels of capital ratio. Then, I perform a crisis-aftermath analysis, where I compare the effects of the shocks during and after the COVID-19 crisis. This subsection concludes with analyzing how expansionary monetary policy influences the effects of the two shocks.

1.5.1 Heterogeneity Analysis

Table 1.5 presents my heterogeneity analysis results. I interact the pandemic shock and the policy shock with a large bank dummy variable which equals to one if a bank has gross total assets greater than $50 billion in 2019. Columns (1)-(3) in Panel A, Table 1.5 contain results for total liquidity creation, asset-side liquidity creation, and liability-side liquidity creation, respectively. The interaction term of the large bank dummy and the pandemic shock has insignificant effects on total bank liquidity creation. On the other hand, the coefficients of the interaction term of the large bank dummy and the policy shock are negative in Columns (1) and (2), suggesting that large banks on average create less liquidity, and the reduction in liquidity creation is from the asset side of the balance sheet although large banks create more liquidity on the liability side. Moreover, the result in Column (4) suggests that the reduction in asset-side liquidity creation is due to increased cash holding. Compared with small banks, large banks have better access to the financial markets, and hence, they have advantages acquiring additional liquidity from the economy over small banks. It is also not surprising that the effect is concentrated on the policy shock not the pandemic shock because banks need to prepare for surged liquidity demand from households which are locked at home due to stringent policies whereas illness does not necessarily cause sudden increase in liquidity demand. The result in Column (5) shows that the coefficient of the pandemic shock is positive and significant whereas the coefficient for the policy shock is negative and insignificant. However, the size of the positive coefficient does not overturn the main effect of the pandemic shock. The results in Columns (6)-(8) suggest that large banks do not create more liquidity from the liability side banking activities.

Panel B Table 1.5 dives deeper into the composition of bank loan portfolios. The coefficients of the interaction terms between the large bank indicator and the two exposures are positive in Column (1) but negative in Column (2). This suggests that compared to small banks, large banks make more Commercial real estate loans and less C&I loans. Moreover, the coefficients of the interaction terms in Column (4) suggest that large banks relatively make less PPP loans under the influence of the two exposures which drives the difference in the effects on total C&I lending between large and small banks. In addition, the overall effect of the two exposures in Column (3) is ambiguous as the interaction terms have opposite signs and similar magnitudes. The result in Column (5) indicates that large banks make more agriculture loans.

In untabulated results, I investigate whether the pandemic shock and the policy shock have differential effects for banks with different levels of capital ratios. Although Berger and Bouwman (2009) show that capital ratio plays a critical role in liquidity creation, I do not find the effects are different across different levels of capital ratios.

1.5.2 Crisis V.S. Aftermath

In this subsection, I distinguish crisis time from aftermath time following (Berger, Karaplan, and Roman, 2023). The results are shown in Table 1.6. I define 2020 as the crisis period and 2021 and 2022 as the recovery period. Built on the main model, I interact a recovery dummy variable with the pandemic shock and the policy shock. The model is the following:

$$LC_{b,t} = \alpha_0 + \alpha_1 * PandemicShock_{b,t} * AfterCOVID_t + \alpha_2 * PolicyShock_{b,t} * AfterCOVID_t + a_3 * AfterCOVID_t + \alpha_4 * PandemicShock_{b,t} + \alpha_5 * PolicyShock_{b,t} + \alpha_6 * StimulusCheckShock_{b,t} + \alpha_7 * PPPShock_{b,t} + \gamma * BankControls_{b,t-1} + \delta * MacroControls_{t-1} + i_b + \epsilon_{b,t}, \quad (6)$$

where *AfterCOVID* is a dummy variable equal to one after 2020 and zero otherwise. Table 1.6 presents the results. In all columnes, the individual effects of the pandemic shock and the policy shock are consistent with my main results, suggesting that the main results are driven by the crisis. Moreover, most of the interaction effects have opposite and significant signs to the individual effects of the pandemic shock and the policy shock. These coefficients indicate a strong reversal of the effects previously observed during the crisis time, which implies a recovery from the crisis. Moreover, the economic significance of the main effects of the pandemic shock are clearly larger than those of the policy shock because these two shocks have very similar standard deviations, but the coefficients of the pandemic shock are much larger than those of the policy shock. This means that a one-standard deviation change of the pandemic shock produces larger change in the dependent variables than the policy shock. However, the coefficients of the interaction terms between recovery and the pandemic shock have opposite signs and much larger magnitude than those of the main effects of the pandemic shock. For total asset-side liquidity creation and total liability-side liquidity creation, the two interaction terms have very similar coefficients. This suggests that the shutdown policies cause smaller disruptions to the economy than the disease during the crisis, however, these policies produce larger recovery post-crisis.

1.6. Conclusion

The COVID-19 pandemic appeared as a black swan in 2020. It instigated two unexpected shocks to the economy and the financial system: its direct effect, called the pandemic shock, and the effect of the policy responses that mandated business closures and regional shutdowns, called the policy shock. In contrast with previous market and financial crises, these two shocks produce much more exogenous changes in the demand for banking services. This paper utilizes the unique setting and examines how banks perform its key function, liquidity creation, differently under the influence of the two shocks.

I find that the two shocks lead to both a quantity reduction and a compositional change in bank liquidity. While banks create less liquidity overall, they produce less liquidity through lending activities and more liquidity through liquid deposits. This reflects that facing direct health threat and the uncertainty in the prospect of economy, bank customers shift their demand for liquidity from future development to ensuring ability to meet immediate needs to make payments. To facilitate potential increased demand for deposit withdrawals, banks hoard liquid assets such as cash and securities, furthering decreasing asset-side liquidity creation. The shift between asset-side quiddity creation and liability-side liquidity creation significantly hurts bank profitability and overall risk.

In additional analysis, my results suggest that large banks create relatively less total liquidity. Specifically, they create much less liquidity from the asset side by raising cash and securities, and they create slightly more liquidity from the liability side. The crisis-aftermath analysis suggests that the effects of both shocks are significantly attenuated after 2020, suggesting a strong recovery. Lastly, I find that expansionary monetary policy significantly alleviates the adverse effect of the pandemic shock.

My results provide insights into the practitioners and the policymakers. First, my results suggest that unbalanced liquidity creation from the asset side and the liability side can be unhealthy to banks. As a result, bankers and policymakers should pay attention to not only how much liquidity is created, but also where and how it is created. Also, the literature tends to focus on how monetary policy and fiscal policy should coordinate during a crisis, and my results show that the coordination between monetary policy and administrative policy is critical. The fast recovery from the COVID-19 crisis can be attributed to the fact that appropriate expansionary monetary policy reduced the unfavorable consequences of shutdowns and closures. These results suggest to the policymakers that in a future crisis, they might also need to consider the interaction between administrative policy with monetary policy and fiscal policy.

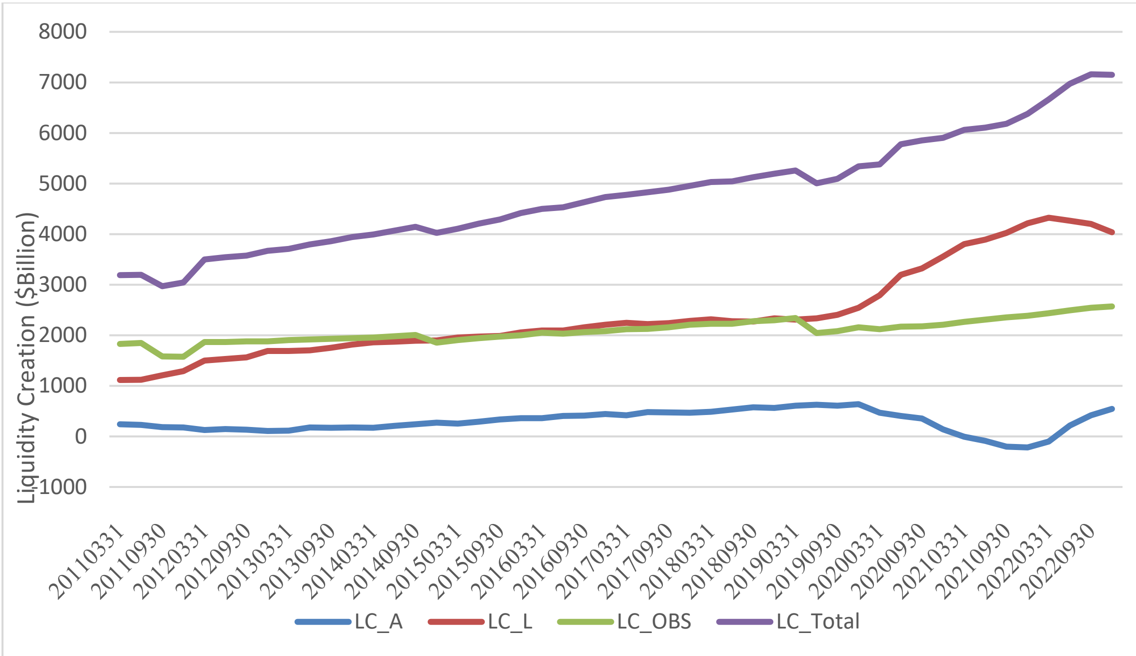


Figure 1.1: Liquidity Creation ($billion) from 2011:Q1-2022:Q4.

Table 1.1: Variable Definitions and Summary Statistics

This Table presents definitions and summary statistics for all variables in my analysis. Panel A lists variable definitions, Panel B displays the summary statistics. The sample period is 2019:Q1-2022:Q4. All variables are winsorized at 1% and 99% level.

Panel A: Variable Definitions

Variable	**Definition**
Key Dependent Variables	
CATFACT/GTA	Total bank liquidity creation divided by gross total assets (GTA). GTA is defined below.
LCA/GTA	Asset-side liquidity creation divided by GTA.
LCL/GTA	Liability-side liquidity creation divided by GTA.
LCOBS/GTA	Off-balance-sheet-side liquidity creation divided by GTA.
Shift	LCL/GTA-LCA/GTA
Other Dependent Variables	
CashSec/GTA	Cash and securities divided by GTA.
FedfndSold/GTA	Federal funds sold divided by GTA.
TotalLoan/GTA	Total loans divided by GTA.
CRE/GTA	Commercial real estate loans divided by GTA.
C&I/GTA	Commercial and industrial loans divided by GTA.
PPP/GTA	Paycheck Protection Program loans divided by GTA.
AgriLoan/GTA	Agricultural loans divided by GTA.
FedfndPrc/GTA	Federal funds purchased divided by GTA.
TranDepo/GTA	Transaction deposits divided by GTA.
SaveDepo/GTA	Savings deposits divided by GTA.
SubordinateDebt/GTA	Subordinated debt divided by GTA.

CapitalRatio	Total equity divided by GTA.
ROA	Return on GTA, calculated as net income divided by GTA.
ROE	Return on equity, calculated as net income divided by total equity.
NII/GTA	Net interest income divided by GTA.
z-score	Calculated as $\frac{CapitalRatio+ROA}{\sigma_{t-4,t}(ROA)}$
<u>Key Independent Variables</u>	
Pandemic Shock	Weighted sum of new COVID cases in states a bank operates in.
Policy Shock	Weighted sum of stringency index[4] in states a bank operates in.
<u>Other Control Variables</u>	
StimulusCheckShock ($Million)	Weighted sum of stimulus checks in states a bank operates in.
PPPShock ($Million)	Weighted sum of PPP loans made by other banks in states a focal bank operates in.
GTA ($Million)	Gross total assets, equals to the sum of total assets, the allowance for loan and lease losses, and the allocated transfer risk reserve.
TotalExpense/GTA	Total expenses divided by GTA.
NPL/GTA	Non-performing loans divided by GTA.
BRW	Monetary shocks by Bu, Rogers, and Wu (2019).
Inflation	Inflation rate.
G_GDP	Gross domestic product growth rate.

[4] Hale, Angrist, Goldszmidt, Kira, Petherick, Phillips, Webster, Goldszmidt, Hallas, Majumdar, and Tatlow (2021).

Panel B: Summary Statistics

Variable	count	mean	std	25%	50%	75%
Key Dependent Variables						
CATFACT/GTA	78588	0.3738	0.1932	0.2547	0.3932	0.5128
LCA/GTA	78588	0.0556	0.1561	-0.0467	0.0687	0.1715
LCL/GTA	78588	0.2555	0.0890	0.2083	0.2682	0.3178
LCOBS/GTA	78588	0.0602	0.0415	0.0305	0.0532	0.0808
Shift	78588	0.1999	0.1895	0.0680	0.1939	0.3265
Other Dependent Variables						
CashSec/GTA	78588	0.3194	0.1655	0.1929	0.2935	0.4184
FedfndSold/GTA	78588	0.0170	0.0427	0	0	0.0110
TotalLoan/GTA	78588	0.6173	0.1621	0.5184	0.6418	0.7404
CRE/GTA	78588	0.2688	0.1386	0.1690	0.2649	0.3617
C&I/GTA	78588	0.0881	0.0712	0.0397	0.0715	0.1166
PPP/GTA	78588	0.0146	0.0364	0	0	0.0142
AgricultureLoan/GTA	78588	0.0423	0.0725	0	0.0065	0.0513
FedfndPrc/GTA	78588	0.0051	0.0146	0.0000	0.0000	0.0000
TranDepo/GTA	78588	0.3104	0.1560	0.1903	0.3281	0.4253
SavDepo/GTA	78588	0.3151	0.1593	0.2088	0.2810	0.3782
SubordinateDebt/GTA	78588	0.0001	0.0010	0	0	0

CapitalRatio	78588	0.1133	0.0461	0.0901	0.1051	0.1253
ROA	78588	0.0026	0.0020	0.0016	0.0026	0.0035
ROE	78588	0.0254	0.0205	0.0146	0.0242	0.0344
NII/GTA	78588	0.0084	0.0021	0.0073	0.0083	0.0093
z-score	59,678	247.55	261.01	84.48	165.60	310.16
<u>Key Independent Variables</u>						
Pandemic Shock	78588	0.0190	0.0283	0.0000	0.0095	0.0245
Policy Shock	78588	0.0295	0.0238	0.0000	0.0245	0.0500
<u>Other Control Variables</u>						
StimulusCheckShock ($Million)	78588	1491.39	5635.93	0	0	0
PPPShock（$Million)	78588	16348.28	83707.52	0	0	73.70
GTA($Million)	78588	4390.38	66504.11	126.83	282.24	696.30
TotalExpense/GTA	78588	0.0205	0.0173	0.0104	0.0178	0.0265
NPL/GTA	78588	0.0170	0.0232	0.0024	0.0091	0.0215
Tighten	78588	0.4399	0.4964	0.0000	0.0000	1.0000
BRW	78588	-0.0063	0.0729	-0.0447	0.0027	0.0275
Inflation	78588	0.1001	0.0483	0.0663	0.0788	0.1107
G_GDP	78588	0.0050	0.0303	-0.0014	0.0067	0.0154

Table 1.2: How does the COVID crisis influence bank liquidity creation I?

This table presents the ordinary least square analysis results for the effects of the pandemic shock and the policy shock on bank liquidity creation. Columns (1)-(3) show the results for total bank liquidity creation (LC_TOTAL/GTA), Columns (4)-(6) show the results for the asset-side liquidity creation (LCA/GTA), Columns (7)-(9) show the results for the liability-side liquidity creation (LCL/GTA), and Column (10) shows the result for off-balance-sheet side liquidity creation (LCOBS/GTA). The main independent variables are the policy shock and the pandemic shock. Control variables, log(GTA), CapitalRatio, ROA, TotalExpense/GTA, NPL/GTA, BRW, Inflation, and G_GDP, are lagged by one period. All regressions control for bank fixed effects. t-statistics are reported in parentheses. The sample period is 2019:Q1-2022:Q4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Dependent Variable:	**LC_TOTAL/GTA**	**LC_TOTAL/GTA**	**LC_TOTAL/GTA**	**LCA/GTA**	**LCA/GTA**	**LCA/GTA**	**LCL/GTA**	**LCL/GTA**	**LCL/GTA**	**LCOBS/GTA**
Pandemic	-0.155***	-0.131***	-0.075***	-0.499***	-0.484***	-0.361***	0.338***	0.359***	0.283***	-0.005*
Shock	(-9.82)	(-13.55)	(-4.71)	(-34.38)	(-49.32)	(-24.59)	(43.39)	(68.69)	(43.66)	(-1.92)
Policy	-0.051***	-0.022***	-0.054***	-0.042***	-0.101***	-0.076***	0.024***	0.082***	0.042***	-0.013***
	(-3.39)	(-2.61)	(-3.74)	(-3.39)	(-13.77)	(-5.93)	(3.55)	(22.06)	(7.03)	(-3.81)
Stimulus		0.078***	0.064***		0.201***	0.178***		-0.114***	-0.104***	-0.012***
Check Shock		(23.64)	(10.10)		(65.42)	(29.88)		(-83.61)	(-45.53)	(-9.56)
PPPShock		-0.005***	0.000		-0.008***	-0.007***		0.003***	0.007***	0.000**
		(-26.09)	(0.70)		(-44.09)	(-19.28)		(37.27)	(44.32)	(2.54)
log(GTA)			-0.026***			-0.070***			0.041***	0.005***

			(-2.65)			(-7.82)			(13.24)	(3.04)
CapitalRatio			-0.497***			-0.041			-0.513***	0.042***
			(-7.53)			(-0.73)			(-17.37)	(3.67)
ROA			0.647***			0.423***			0.313***	0.045*
			(4.50)			(3.47)			(5.60)	(1.86)
TotalExpense/			-0.046			0.060			-0.184***	-0.007
GTA			(-0.71)			(1.18)			(-6.29)	(-0.59)
NPL/GTA			-0.127***			-0.017			-0.085***	-0.022***
			(-3.52)			(-0.47)			(-6.09)	(-3.33)
BRW			-0.031***			-0.015***			-0.012***	-0.001*
			(-14.10)			(-8.92)			(-11.48)	(-1.66)
Inflation Rate			0.309***			-0.057***			0.305***	0.052***
			(14.54)			(-2.99)			(32.84)	(14.07)
G_GDP			0.012			0.015**			-0.007**	0.005***
			(1.51)			(1.96)			(-2.21)	(2.91)
Adj. R^2	0.001	0.920	0.928	0.008	0.895	0.901	0.012	0.855	0.928	0.904
N	78588	78583	78583	78588	78583	78583	78588	78583	78583	78583

BankFE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes

Table 1.3: How does the COVID crisis influence bank liquidity creation II?

This table presents the ordinary least square analysis results for the effects of the pandemic shock and the policy shock on the components of bank liquidity creation. Panel A presents the main asset-side and liability-side liquidity creation components. The asset-side components are contained in Columns (1)-(3). The dependent variables are cash and securities (CashSec/GTA), federal funds sold (FedFndSold/GTA), and total loans (TotalLoan/GTA), respectively. The liability-side components are shown in Columns (4)-(7). The dependent variables are federal funds purchased (FedFndPrc/GTA), transaction deposits (TranDepo/GTA), savings deposits (SavDepo/GTA), and capital ratio (CapitalRatio), respectively. Panel B shows the results for all types of bank loans that are components of bank liquidity creation. They are commercial real estate loans (CRA/GTA), commercial and industrial loans (C&I/GTA), C&I loans that are not in the Paycheck Protection Program (PPP, C&INoPPP/GTA), PPP loans (PPP/GTA), agricultural loans (AgriLoan/GTA), and all other loans (Other/GTA), respectively. The main independent variables are the policy shock and the pandemic shock. Control variables, log(GTA), CapitalRatio, ROA, TotalExpense/GTA, NPL/GTA, BRW, Inflation, and G_GDP, are lagged by one period. All regressions control for bank fixed effects. t-statistics are reported in parentheses. The sample period is 2019:Q1-2022:Q4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Dependent Variable:	**CashSec/GTA**	**FedFndSold/GTA**	**TotalLoan/GTA**	**FedFndPrc/GTA**	**TranDepo/GTA**	**SavDepo/GTA**	**CapitalRatio**
Pandemic Shock	0.447***	0.031***	-0.452***	-0.002*	0.421***	0.123***	-0.026***
	(25.01)	(6.50)	(-25.47)	(-1.90)	(30.60)	(10.72)	(-10.22)
Policy Shock	0.077***	0.051***	-0.113***	-0.001	0.041***	0.034***	-0.010***

	(4.71)	(8.66)	(-7.30)	(-1.08)	(3.16)	(3.34)	(-3.28)
StimulusCheckShock	-0.194***	-0.017***	0.206***	0.000	-0.155***	-0.049***	0.004***
	(-28.52)	(-7.26)	(30.69)	(0.33)	(-27.23)	(-9.45)	(3.13)
PPPShock	0.009***	0.001***	-0.010***	0.000	0.012***	0.002***	-0.001***
	(19.77)	(8.22)	(-21.40)	(0.34)	(31.38)	(7.52)	(-11.75)
log(GTA)	0.087***	0.003	-0.081***	-0.002***	0.079***	-0.002	-0.005***
	(8.46)	(1.17)	(-7.74)	(-6.24)	(11.35)	(-0.45)	(-4.01)
CapitalRatio	-0.019	0.079***	-0.094	-0.010***	-0.110**	-0.144***	0.748***
	(-0.30)	(4.35)	(-1.44)	(-6.15)	(-2.53)	(-4.80)	(36.21)
ROA	-0.545***	-0.045	0.660***	-0.011	0.419***	0.298***	0.048*
	(-3.84)	(-0.96)	(4.65)	(-1.51)	(3.70)	(2.74)	(1.68)
TotalExpense/GTA	-0.118*	0.027	0.021	0.005	-0.308***	-0.104***	-0.049***
	(-1.67)	(1.43)	(0.31)	(1.45)	(-6.08)	(-3.18)	(-3.45)

NPL/GTA	0.004	0.024	-0.046	-0.000	-0.033	-0.073***	0.044***
	(0.09)	(1.27)	(-1.13)	(-0.03)	(-1.20)	(-2.80)	(8.12)
BRW	0.015***	0.002*	-0.013***	-0.000	-0.012***	-0.007***	0.006***
	(6.06)	(1.90)	(-5.63)	(-0.69)	(-6.39)	(-5.20)	(9.74)
Inflation Rate	0.091***	-0.016**	-0.115***	0.011***	0.483***	0.072***	-0.051***
	(4.16)	(-2.46)	(-5.25)	(8.18)	(28.33)	(4.98)	(-11.30)
G_GDP	-0.005	-0.012***	0.010	0.002***	0.013*	0.015***	0.041***
	(-0.57)	(-3.91)	(1.20)	(3.34)	(1.94)	(2.69)	(22.66)
Constant	-0.800***	-0.026	1.672***	0.029***	-0.739***	0.352***	0.102***
	(-6.05)	(-0.93)	(12.52)	(7.56)	(-8.21)	(5.24)	(5.57)
Adj. R^2	0.882	0.623	0.888	0.836	0.847	0.862	0.939
N	78583	78583	78583	78583	78583	78583	78583
BankFE	Yes						

Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable:	**CRE/GTA**	**C&I/GTA**	**C&INoPPP/ GTA**	**PPP/GTA**	**AgriLoan/GTA**	**OTHER/GTA**
Pandemic Shock	-0.155***	-0.010**	-0.061***	0.051***	-0.045***	-0.001
	(-15.66)	(-2.03)	(-11.32)	(8.02)	(-18.54)	(-0.86)
Policy Shock	-0.078***	0.111***	-0.045***	0.156***	-0.038***	0.005***
	(-8.54)	(20.44)	(-10.61)	(28.09)	(-16.49)	(3.53)
StimulusCheckShock	0.020***	0.083***	0.009***	0.074***	0.034***	0.001**
	(4.72)	(33.53)	(3.92)	(24.64)	(26.73)	(2.21)
PPPShock	-0.005***	0.003***	-0.002***	0.006***	-0.002***	-0.000**
	(-18.91)	(23.16)	(-15.60)	(29.68)	(-26.72)	(-1.97)
log(GTA)	-0.032***	-0.001	-0.024***	0.023***	-0.011***	-0.001
	(-4.82)	(-0.35)	(-7.48)	(5.80)	(-9.93)	(-0.98)
CapitalRatio	0.013	-0.080***	0.002	-0.082***	-0.001	0.005
	(0.29)	(-4.43)	(0.09)	(-3.46)	(-0.15)	(1.17)
ROA	0.349***	-0.080	0.124**	-0.204***	0.675***	0.035

	(3.98)	(-1.31)	(2.26)	(-2.61)	(10.54)	(0.85)
TotalExpense/GTA	-0.018	0.009	0.031**	-0.022	0.003	-0.005*
	(-0.56)	(0.45)	(1.97)	(-0.97)	(0.63)	(-1.70)
NPL/GTA	-0.006	-0.054***	0.013	-0.067***	0.054***	-0.004
	(-0.25)	(-3.26)	(0.89)	(-4.81)	(4.45)	(-1.16)
BRW	-0.001	-0.008***	-0.001*	-0.006***	-0.002***	0.001***
	(-0.79)	(-12.52)	(-1.77)	(-9.10)	(-6.25)	(3.00)
Inflation Rate	0.108***	-0.118***	0.041***	-0.159***	-0.059***	0.002
	(8.09)	(-14.50)	(4.30)	(-12.80)	(-17.88)	(1.11)
l_G_GDP	0.018***	-0.004	0.002	-0.006	-0.010***	0.002***
	(3.14)	(-1.40)	(0.58)	(-1.55)	(-8.60)	(3.09)
Constant	0.670***	0.114***	0.374***	-0.260***	0.185***	0.014
	(7.84)	(2.92)	(9.40)	(-5.36)	(12.65)	(1.50)
Adj. R^2	0.940	0.870	0.899	0.527	0.953	0.906
N	78583	78583	78583	78583	78583	78583
BankFE	Yes					

Table 1.4: The effects of the Shift on Bank Performance

This table presents the results for the effects of the two COVID shocks on bank performance. I use bank profitability and bank risk to measure bank performance. Bank profitability is measured by return on gross total assets (ROA), return on equity (ROE), and net interest income (NII/GTA). Bank risk is measured by z-score. The left panel shows the results of ordinary least square analysis. Bank controls include StimulusCheckShock, PPPShock, log(GTA), CapitalRatio, ROA, TotalExpense/GTA, and NPL/GTA. Macro controls include BRW, Inflation, and G_GDP. These control variables are lagged by one period. All regressions control for bank fixed effects. t-statistics are reported in parentheses. The sample period is 2019:Q1-2022:Q4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**
	ROA	**ROE**	**NII/GTA**	**Z-Score**
Pandemic Shock	-0.002***	-0.008***	-0.005***	-227.415***
	(-6.74)	(-2.94)	(-21.25)	(-5.47)
PolicyShock	-0.004***	-0.036***	-0.005***	-243.086***
	(-12.49)	(-11.53)	(-19.37)	(-4.29)
Other Policies	Yes			
Bank Controls	Yes			
Macro Controls	Yes			
Constant	0.001	0.023*	0.020***	702.801***
	(0.52)	(1.85)	(13.51)	(4.19)
Adj. R^2	0.528	0.509	0.811	0.168
N	78583	78583	78583	59624

BankFE	Yes

Table 1.5: Heterogeneity Analysis

This table presents the results of heterogeneity analysis for bank size. LargeBank is a dummy variable equal to one if a bank has size over $50 billion by the end of 2019. Columns (1)-(3) Panel A show the results for total bank liquidity creation (LC_TOTAL/GTA), the asset-side liquidity creation (LCA/GTA), and the liability-side liquidity creation (LCL/GTA). The main asset-side components are contained in Columns (4)-(5). The dependent variables are cash and securities (CashSec/GTA) and total loans (TotalLoan/GTA), respectively. The liability-side components are shown in Columns (6)-(8). The dependent variables are transaction deposits (TranDepo/GTA), savings deposits (SavDepo/GTA), and capital ratio (CapitalRatio), respectively. Panel B shows the results for main types of bank loans that are components of bank liquidity creation. They are commercial real estate loans (CRA/GTA), commercial and industrial loans (C&I/GTA), C&I loans that are not in the Paycheck Protection Program (PPP, C&INoPPP/GTA), PPP loans (PPP/GTA), and agricultural loans (AgriLoan/GTA), respectively. Bank controls include StimulusCheckShock, PPPShock, log(GTA), CapitalRatio, ROA, TotalExpense/GTA, and NPL/GTA. Macro controls include BRW, Inflation, and G_GDP. These control variables are lagged by one period. All regressions control for bank fixed effects. t-statistics are reported in parentheses. The sample period is 2019:Q1-2022:Q4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	LC_TOTAL/GTA	**LCA/GTA**	**LCL/GTA**	**CashSec/GTA**	**TotalLoan/GTA**	**TranDepo/GTA**	**SavDepo/GTA**	**CapitalRatio**
LargeBank*Pandemic Shock	0.048	0.144*	0.002	-0.084	0.231***	0.225	-0.249	0.011
	(0.51)	(1.94)	(0.05)	(-0.94)	(2.78)	(1.12)	(-1.22)	(1.30)
LargeBank*Policy Shock	-0.315***	-0.215***	0.170**	0.288***	-0.071	0.139	0.216	-0.013
	(-3.32)	(-3.33)	(2.06)	(2.84)	(-1.19)	(0.65)	(1.28)	(-0.77)

Pandemic Shock	-0.081***	-0.368***	0.284***	0.454***	-0.461***	0.420***	0.124***	-0.027***
	(-5.13)	(-25.13)	(43.59)	(25.45)	(-26.03)	(30.46)	(10.70)	(-10.69)
Policy Shock	-0.033**	-0.056***	0.043***	0.054***	-0.086***	0.042***	0.037***	-0.006**
	(-2.19)	(-4.15)	(7.09)	(3.16)	(-5.38)	(3.27)	(3.70)	(-2.12)
Bank Controls	Yes							
Macro Controls	Yes							
Constant	0.712***	0.950***	-0.247***	-0.784***	1.653***	-0.752***	0.344***	0.101***
	(5.71)	(8.35)	(-6.18)	(-6.01)	(12.56)	(-8.35)	(5.14)	(5.61)
Adj. R^2	0.928	0.902	0.928	0.883	0.889	0.847	0.862	0.939
N	78583	78583	78583	78583	78583	78583	78583	78583
BankFE	Yes							

Panel B	(1)	(2)	(3)	(4)	(5)
	CRE/GTA	**C&I/GTA**	**C&INoPPP/GTA**	**PPP/GTA**	**AGRILoan/GTA**
LargeBank*Pandemic Shock	0.113***	-0.091***	-0.072**	-0.019***	0.062***
	(4.35)	(-2.80)	(-2.30)	(-4.15)	(15.04)
LargeBank* Policy Shock	0.256***	-0.356***	0.087**	-0.442***	0.060***
	(10.59)	(-9.63)	(2.21)	(-10.30)	(13.37)
Pandemic Shock	-0.158***	-0.011**	-0.062***	0.051***	-0.046***
	(-16.01)	(-2.07)	(-11.55)	(8.16)	(-18.60)
Policy Shock	-0.068***	0.113***	-0.042***	0.155***	-0.039***
	(-7.10)	(20.64)	(-9.70)	(27.12)	(-16.53)
Bank Controls	Yes				
Macro Controls	Yes				
Constant	0.660***	0.117***	0.371***	-0.254***	0.185***
	(7.76)	(2.99)	(9.48)	(-5.34)	(12.65)
Adj. R^2	0.940	0.870	0.899	0.527	0.953
N	78583	78583	78583	78583	78583
BankFE	Yes				

Table 1.6: Crisis-Aftermath Analysis

This table presents the results for the crisis-aftermath analysis results. AfterCOVID is a dummy variable equal to one if year is greater than 2020, or zero otherwise. Columns (1)-(3) Panel A show the results for total bank liquidity creation (LC_TOTAL/GTA), the asset-side liquidity creation (LCA/GTA), and the liability-side liquidity creation (LCL/GTA). The main asset-side components are contained in Columns (4)-(5). The dependent variables are cash and securities (CashSec/GTA) and total loans (TotalLoan/GTA), respectively. The liability-side components are shown in Columns (6)-(8). The dependent variables are transaction deposits (TranDepo/GTA), savings deposits (SavDepo/GTA), and capital ratio (CapitalRatio), respectively. Panel B shows the results for main types of bank loans that are components of bank liquidity creation. They are commercial real estate loans (CRA/GTA), commercial and industrial loans (C&I/GTA), C&I loans that are not in the Paycheck Protection Program (PPP, C&INoPPP/GTA), PPP loans (PPP/GTA), and agricultural loans (AgriLoan/GTA), respectively. Bank controls include StimulusCheckShock, PPPShock, log(GTA), CapitalRatio, ROA, TotalExpense/GTA, and NPL/GTA. Macro controls include BRW, Inflation, and G_GDP. These control variables are lagged by one period. All regressions control for bank fixed effects. t-statistics are reported in parentheses. The sample period is 2019:Q1-2022:Q4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A	**LC_TOTAL/ GTA**	**LCA/ GTA**	**LCL/ GTA**	**CashSec/ GTA**	**TotalLoan/ GTA**	**TranDepo/ GTA**	**SavDepo/ GTA**	**Capital Ratio**
AfterCOVID*Pandemic Shock	0.017	0.533***	-0.526***	-0.655***	0.664***	-0.718***	-0.162***	0.180***
	(0.97)	(33.11)	(-65.39)	(-34.80)	(37.26)	(-35.86)	(-8.21)	(30.34)
AfterCOVID*Policy Shock	0.396***	0.863***	-0.383***	-0.950***	0.914***	-0.363***	-0.409***	0.007

	(8.43)	(21.74)	(-19.38)	(-19.85)	(21.12)	(-6.79)	(-7.88)	(0.43)
Pandemic Shock	0.012	-0.463***	0.498***	0.595***	-0.596***	0.725***	0.120***	-0.153***
	(0.76)	(-32.06)	(71.35)	(35.18)	(-36.77)	(40.51)	(6.75)	(-30.60)
Policy Shock	-0.090***	-0.124***	0.031***	0.120***	-0.157***	0.023***	0.043***	0.000
	(-11.16)	(-18.03)	(9.46)	(14.61)	(-20.65)	(3.17)	(6.22)	(0.14)
AfterCOVID	-0.038***	-0.098***	0.054***	0.109***	-0.110***	0.077***	0.031***	-0.002**
	(-9.01)	(-28.64)	(36.48)	(26.55)	(-27.52)	(24.11)	(10.15)	(-2.51)
Bank Controls					Yes			
Macro Controls					Yes			
Constant	0.333***	0.059***	0.215***	0.309***	0.627***	0.255***	0.311***	0.134***
	(329.18)	(69.60)	(464.71)	(319.55)	(663.11)	(234.46)	(283.28)	(343.27)
Adj. R^2	0.926	0.914	0.934	0.897	0.905	0.857	0.863	0.845
N	78583	78583	78583	78583	78583	78583	78583	78583
BankFE					Yes			

	(1)	(2)	(3)	(4)	(5)
Panel B	**CRE/ GTA**	**C&I/GTA**	**C&INoPPP/GTA**	**PPP/GTA**	**AGRILoan/GTA**
AfterCOVID*	0.398***	-0.270***	0.219***	-0.489***	0.159***
Pandemic Shock	(37.10)	(-26.19)	(25.47)	(-38.49)	(32.58)
AfterCOVID*	0.021	0.512***	-0.023	0.535***	0.228***
Policy Shock	(0.72)	(25.27)	(-1.50)	(30.93)	(19.49)
Pandemic Shock	-0.376***	0.273***	-0.209***	0.482***	-0.109***
	(-38.76)	(27.86)	(-25.56)	(38.98)	(-29.33)
Policy Shock	-0.037***	0.010***	-0.018***	0.028***	-0.043***
	(-7.75)	(2.63)	(-6.32)	(8.13)	(-21.14)
AfterCOVID	-0.031***	-0.018***	-0.014***	-0.003***	-0.021***
	(-26.99)	(-25.96)	(-24.38)	(-7.14)	(-32.75)
Bank Controls			Yes		
Macro Controls			Yes		
Constant	0.267***	0.084***	0.076***	0.008***	0.043***
	(387.94)	(229.92)	(223.24)	(43.93)	(194.42)
Adj. R^2	0.942	0.873	0.900	0.531	0.956
N	78583	78583	78583	78583	78583

BankFE	Yes

CHAPTER 2: BANK-BORROWER RELATIONSHIPS FROM SUPPLY-CHAIN RELATIONSHIPS: A NETWORK APPROACH

Abstract

In the financial world, bank-borrower relationships are key conduits through which banks provide the "specialness" that helps drive the real economy. Banks use their relationships to gather and process information from their borrowers over the course of their relationships, especially soft private information such as the moral character of firm management. Banks use the relationship lending technology to provide credit to firms of all types, but especially to bank-dependent firms with insufficient quality hard information to qualify for credit otherwise.

2.1. Introduction

The relationship lending literature considers bank-borrower relationships as exogenously given and investigates the implications of bank-borrower relationships on loan terms, as well as the effects on banks and firms directly involved in the relationships. However, two fundamental questions have been long overlooked: What are the origins of bank-borrower relationships, and do these different origins influence banks' treatment of their relationship borrowers? Answers to these questions may provide key insights into the ability of banks to provide the specialness that drives the real economy, whether banking resources are allocated efficiently, and where policy and research attention to these relationship origins might be best directed.

Since bank-borrower relationships are based on information, the search for answers to these fundamental questions leads me to supply-chain relationships, a different type of vital economic relationship that is rich with information. Similar to bank-borrower relationships, supply-chain relationships allow firms to acquire and process private soft information from one another over the course of their relationships. In this paper, I find that supply chain relationships do create bank-borrower relationships in the form of multilevel closure where firms borrow from the banks of their supply chain partners. These bank-borrower relationships bring about relatively favorable terms for borrowers on syndicated loans—lower interest spreads, larger amounts, and longer maturities. Surprisingly, these benefits occur only when the multilevel closure is achieved with participants in loan syndicates as opposed to with lead banks.

If I were to address these questions in a traditional econometric framework, I would regress loan contract terms on a bank-borrower relationship existence dummy and use a plausibly exogenously supply chain shock as the instrument. In the first stage regression, I answer the question of whether the supply chain is an origin of the bank-borrower relationship, and the second stage coefficient on the predicted value would answer the second question of whether these borrowers benefit from the relationships derived from the supply chain origin.

However, such a traditional approach would be problematic under this circumstance for three reasons. First, supply chain shocks might not be exogenous to bank-borrower relationships because I cannot rule out the possibility that bank-borrower relationships might also foster supply-chain relationships. Second, any supply-chain shock to borrowers would almost certainly influence the borrowers' riskiness and other characteristics, which would direct impact loan contract terms, violating the exclusion restriction. Third, in general, relationships in the same or different but overlapping networks are likely to correlate with each other through various network structures[1] (e.g., Wasserman and Faust, 1994; Snijders and Baerveldt, 2003; Entwisle, Faust, Rindfuss, and Kaneda, 2007). Therefore, any shock that is exogenous to one particular supply-chain relationship may also impact other supply-chain relationships that influence the bank-borrower relationship of interest, and thus, the exclusion restriction is violated.

I address these endogeneity issues using a novel method, stochastic actor-oriented models (SAOMs). Jackson, Rogers, Zenou (2017) suggest that relationship formation cannot be modeled on a relationship-by-relationship basis but on a structural basis where relevant network structures are accounted for, and SAOMs are one approach they suggest. SAOMs are designed to model relationship evolution in networks by explicitly modeling network structural effects that give rise to interdependences among relationships (Snijders 2001, 2005, 2017; Snijders, Steglich, and Schweinberger, 2007)[2]. There are two main advantages of SAOMs: first, it is the only model dealing with evolution of relationships in two or more different networks. This is critical to my paper because modeling coevolution of bank-borrower relationships and supply-chain relationships helps address the reverse causality issue. Second, SAOMs allow to control for a wide range of structural effects. Using panel data on bank lending networks and supply chain networks from 2015 to 2019,

[1] Network Structures refer to graph-theoretic patterns of multiple relationships and/or actors of networks. For example, triadic closure is a network structure refers to two actors connected with common third parties tend to connect with each other, or "being friend with my friend's friend". Another example could be homophily, which refers to the tendency that similar actors tend to connect with each other and potentially become more similar.
[2] SAOMs are described in greater detail in section 4.

I model the simultaneous evolution of the two types of networks to investigate this unique origination of bank-borrower relationships.

I particularly focus on multilevel closure in the bank lending networks, controlling for network structure effects. The multilevel closure effect refers to the tendency that the focal firms connect with banks that have pre-existing bank-borrower relationships with their supply chain partners, and these supply chain partners can either be suppliers or customers of the focal firms. Figure 2.1 gives a graphical illustration of the closure effect. Multilevel closure can be formed at least in three ways. First, a supply chain partner of a focal firm can refer the banks it has good experience with and the focal firm to each other[3] when the supply chain partner discovers that the focal firm may have credit demand through regular communications, delayed payments, or urgent payment requests. Also, in general, closure facilitates information generation, transmission, and validation among connected entities[4]. In the case of this paper, the banks of a focal firm's supply chain partners can gather and validate information of the focal firm from the supply chain partners. Also, the focal firm can observe the treatment of its supply chain partners by their relationship banks and approach the most suitable banks when it has credit demand. The SAOM results suggest that there is significant evidence for the multilevel closure effect controlling for other structural effects and borrower and bank characteristics. A firm is around 54% more likely to form a bank-borrower relationship with a customer's bank or a supplier's bank. This means that supply-chain relationships can be an origin for bank-

[3] Papers discussing referral are, for example, Burt and Knez, 1995; Fafchamps, Goyal, and van der Leij, 2010; Granovetter, 1973.
[4] Papers discussing details of such feature of closure are, for example, Kogut and Walker, 2001; Lomi and Pattison, 2006; Phelps, 2010; Nahapiet and Ghoshal, 1998; Ahuja, 2000; Dyer and Nobeoka, 2000; Schilling and Phelps, 2007.

borrower relationships when the supply chain partners of a borrower have existing bank-borrower relationships with banks.

In the second stage of empirical analysis, I develop measures for the multilevel closure effect to capture this particular origin of bank-borrower relationships and use ordinary least square (OLS) regression analysis to study its implications to the treatment of relationship borrowers in terms of loan spread, amount, maturity, covenant, and collateral requirement. Following the market flex model (Zhang, Zhang, and Zhao, 2022), I distinguish the effects of lead banks and participant banks in for syndicated loans because the model contents that lead banks and participant banks play different roles in loan syndication. I define a lead bank, or more generally a bank that directly underwrite a loan syndicate as a "closure lead bank" if the bank has pre-existing bank-borrower relationships with the supply chain partners of the borrower. Similarly, I define a participant bank as a "closure participant bank" if a participant bank in a loan syndicate also has pre-existing bank-borrower relationships with the supply chain partners of the borrower. I find that borrowers are treated worse in terms of higher spreads, lower loan amounts, and shorter maturities when closure lead bank presents. Surprisingly, when a loan syndicate has closure participant banks, the loan tends to be cheaper and larger with longer maturity. In addition, the effects of both closure lead banks and closure participant banks on loan spreads are significantly greater for term loans than credit lines, which is consistent with the market flex model since making credit lines requires more private information, ceteris paribus, therefore, lead banks that lend credit lines are less sensitive to private information.

This paper contributes to several strands of literature. To start with, it adds to the relationship lending literature from three aspects. First, most relationship lending research takes bank-borrower relationships as exogenously given. See Boot (2000), Degryse and Ongena (2008), and the meta-analysis by Kysucky and Norden (2016) for literature reviews. An exception is Schwert (2018). The author uses a two-sided matching model to characterize relationship formation between banks and borrowers. However, this model ignores supply-chain relationships between borrowers and many network structural effects which could also foster bank-borrower relationships. This paper is the first to model the origination of bank-borrower relationships from a network perspective and document evidence that relationships outside of the bank lending networks, namely supply-chain relationships, can cultivate new bank-borrower relationships. Second, I contribute to the discussion about the bright side and dark side of relationship lending. Some research finds that firms benefit from their bank-borrower relationships in terms of favorable loan terms (e.g, Petersen and Rajan, 1994; Berger and Udell, 1995; Cole, 1998; Elsas and Krahnen, 1998; Harhoff and Körting, 1998; Degryse and Ongena, 2005; Bharath, Dahiya, Saunders, and Srinivasan, 2011; Prilmeier, 2017; López-Espinosa, Mayordomo, and Moreno, 2017). Other studies find that private information banks acquired from lending relationships lead to hold up problems. As a result, firms get worse loan terms (Angelini, Di Salvo, and Ferri, 1998; Degryse and Van Cayseele, 2000; Chakraborty and Hu, 2006; Degryse and Van Cayseele, 2000; Hernández-Cánovas and Martínez-Solano, 2010). I find that the origin of a bank-borrower relationship and the role a bank plays in a syndicated loan jointly determine whether a bank reveals its dark side or bright side. A bank treats its relationship borrowers worse when it is the lead bank of the borrowers' loan syndicates and has pre-existing relationships with the borrowers' supply chain partners. In contrast, a bank treats its relationship borrowers better when it is a participant bank of the borrowers' loan syndicates and has pre-existing relationships with the borrowers' supply chain partners. Third, most relationship lending papers concerning syndicated loans concentrate on lead banks (e.g., Sufi, 2007; Ivashina, 2009). An exception is Zhang, Zhang, and Zhao (2022). They use a market flex model approach and argue that lead banks strategically underprice loans to induce informed participant banks to reveal their private information. The results support their model predictions and show participant banks can play an important role in the loan pricing process.

This paper also adds to the literature about the financial implications of business relationships. For example, Campello and Gao (2017) and Cen, Dasgupta, Elkamhi, and Pungaliya (2016) find that customer characteristics have significant influence over their suppliers' loan terms. Moreover, Giacomini, Kumar, and Naranjo (2022) find that common banks strengthen supply chain relationships. My paper differentiates from these papers from three aspects: first, I model evolution of both supply-chain relationships and bank-borrower relationships simultaneously. Second, I focus on the effects of banks in loan syndicates whereas these papers study the effects of supply-chain partners. Third, I identify a specific social structure that drives bank-borrower relationship formation and explain dynamics of banks' roles in syndicated loan pricing. Moreover, Cohen and Frazzini (2008) show that stock prices do not timely reflect news about firms connected along supply chain, which gives rise to stock return predictability. Agca, Babich, Birge, and Wu (2021) find that economically connected firms experience co-movements in their credit default swap spreads. Anton and Polk (2014) find that the degree of common ownership can predict in stock return correlation. These papers study the financial market implications of firms either economically connected along the supply chain or financially connected through common equity owners. Houston, Lin, and Zhu (2016) study how a customer's bankruptcy substantially increases the cost of its suppliers' bank loans. This paper studies the implications of multilevel closure, a network structure consisting of both supply-chain relationships and bank-borrower relationships, to loan terms of borrowers in such structures.

The rest of this paper is organized as the following: section 2 discusses sample construction and presents variable definitions and summary statistics. Section 3 defines and describes bank lending networks and supply chain networks. Section 4 gives a nontechnical description of stochastic actor-oriented models (SAOMs) and displays the results of SAOMs. Section 5 shows the ordinary least square regression analysis results for the implications of multilevel closure effects to bank loan terms, section 6 addresses endogeneity concerns, and section 7 concludes.

2.2. Sample Construction, Variable Definitions, and Summary Statistics

In this section, I discuss the sample construction and show the definitions of variables and summary statistics. The data comes from four sources. I acquire bank loan, mostly syndicated loan data from DealScan. I obtain supply-chain relationships data from Compustat historical customer segment. The financial data of borrowers in DealScan is acquired from Compustat, and I use the linking table from Chava, Sudheer, and Michael R. Roberts (2008) and update the link until 2020. I financial data of commercial banks from Call Reports then aggregate the data to the ultimate parent level, that is if a bank is held by a bank holding company, I find the ultimate bank holding company (BHC) of the bank and aggregate the data to the ultimate BHC. If a bank stands alone, then I consider it is the ultimate holder of itself. In this paper, I focus on loans recorded in DealScan that have at least one bank lender and were made to firms that can be matched to both Compustat and

Compustat historical customer segment. The sample period is between 2015 to 2019 for the SAOM estimation in Sections 3 and 4, and 2001 to 2020 for the ordinary least square regression analysis in Sections 5 and 6. I choose a shorter sample period for SAOM estimation because the SAOM estimation is highly computationally demanding, and it would take weeks or even months for the algorithm to converge. I choose to stop in 2019 to avoid the impact of COIVID-19 crisis and the policy responses to the bank lending networks and supply chain networks. In the end, I have 12,534 unique loans, 6,771 unique borrowers, and 474 unique banks in the sample. Table 1.1 displays variable definitions and summary statistics. All variables are winsorized at 1% and 99% except for dummy variables and count variables. I defer the description of out networks to the next section.

The main independent variables are Closure, ClosureLead, ClosureParti and CountClosureParti. Closure is a dummy variable equal to one if at least one bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise. ClosureLead is a dummy variable equals to one if the lead bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise. ClosureParti is a dummy variable equals to one if at least one participant bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise. CountClosureParti is the number of participant banks in a loan syndicate that also lend to the supply chain partners of the borrower in the past three years. There is no count variable for the number of closure lead banks because there is only one lead bank per loan syndicate, so the count variable is the same as ClosureLead. I distinguish and measure the effects of multilevel closure with banks taking different roles in loan syndicates. The extant literature on syndicated loans stresses the importance of lead banks as they collect information, perform due diligence, lead negotiation with borrowers, and lend the largest share of loans (e.g., Sufi, 2007; Ivashina, 2009). However, according to Benveniste and Spindt (1989) and the market flex model in Zhang, Zhang, Zhao (2022), lead banks can use underpricing to incentivize participant banks to reveal their private information. The setting of this paper is a specific case where closure participant banks are highly likely to have private information that lead banks do not because they are connected with the supply chain partners of the borrowers that lead banks do not. Therefore, it is sensible to distinguish the effects of closure participant banks and closure lead banks.

The summary statistics for Closure, ClosureLead, and ClosureParti indicate some interesting facts in the data. For loans lent to borrowers with suppliers or customers identified in Compustat histiorical customer segment data, 73% has at least one closure bank, and 61% loans' lead banks are closure banks, and some of the participant banks in 61% loans are closure banks, which is very close to the percentage of lead closure banks. This means that borrowing from supply chain partners' banks are not uncommon.

2.3. Bank Lending Networks and Supply Chain Networks

2.3.1 Bank Lending Networks

The bank lending networks in this paper are two-mode networks observed annually from 2015 to 2019 from DealScan. The two modes are banks and borrowers. The banks consist of U.S. bank holding companies and stand-alone commercial banks, and the borrowers are firms publicly listed on major U.S. equity markets, excluding financial companies. Banking relationships arise through bank loans including both traditional one-to-one loans and syndicated loans[5]. If there is at least one loan made, at least partially, from

[5] A syndicated loan is a loan made by more than one banks. Typically, lead banks and participant banks form a syndicate and lend a bundle of different types of loans, called a package, to a borrower. Banks can decide their contributions to each loan in a package, or not to participate in some loans at all. Lead banks are responsible for originating, negotiating, and monitoring the loan package.

a bank to a firm, then there is a bank lending relationship between the bank and the firm. I assume a lending relationship last until all loans between the firm and the bank involved in this relationship matures. This assumption can be strong because many banks, especially participant banks, may not hold their loans to maturity. However, due to data limitations, I do not know when a bank sells all loans with a borrower in the secondary market, so this assumption is necessary, and I do admit it is not perfect.

There are 1,990 borrowers and 262 banks in the networks observed from 2015-2019. I choose this period to avoid the potential effect of COVID-19 crisis to the network structures. To make the size of the bank lending networks manageable, in the main SAOM estimation, I exclude firms that only borrow once from 2015-2019 because they are likely to be a "one-time shopper" and do not intend to establish banking relationships, at least not in these networks. As the result, I have 857 borrowers and 195 banks in the bank lending networks. In the robustness check, I add them back, and the results are not affected. Summary statistics of the bank lending networks are presented in Panels A and B in Table 2.2.

Moreover, although literature has found the function of lead banks is very different from participant banks in syndicated loans (e.g., Sufi, 2007; Ivashina, 2009), I do not distinguish them in the SAOM estimation, because, first, I assume that each bank-firm pair decides whether to start a new relationship or terminate an existing relationship then decides what role the bank should play. In other words, the roles of banks in loan syndicates do not directly influence relationship evolution. Second, banks may take different roles in different loans to the same firm in a given year while lending relationships are observed annually. Hence, it is necessary to aggregate the bank role information to the same level, which would introduce noises to model estimation, which is highly undesirable as SAOM is extremely computationally demanding. I do acknowledge that the distinctions between lead banks and participant banks can be potentially important to lending relationship evolution, and it will be included in analysis in the future.

2.3.2 Supply Chain Networks

The supply chain networks in this paper are one-mode networks of borrowers in the bank lending networks observed annually from 2015 to 2019. The mode is firms appearing in the bank lending networks. Firms can be suppliers and customers at the same time. The relationship information is acquired from Compustat historical customer segments data, where supplying firms report the customers, whose purchases account for 10% or more of the suppliers' sales, according to FASB Accounting Standards Codification Topic 280 (ASC 280) requirements. There is one limitation with this dataset: it reports important customers of suppliers, but it does not report all important suppliers of customers. In other words, I do not observe all important customer-supplier relationships from that dataset. This limitation is acceptable because the supply chain networks are not the focus of this paper, and although I cannot capture all multilevel closures, the closures I identified are reliable.

The summary statistics for the supply chain networks are presented in Panels C and D in Table 2.2. Notably, these networks are extremely sparse as most firms do not have report any supplier or customer over the sample period. This is due to the limitation of Compustat historical customer segments data because it only reports important customers to suppliers, not important suppliers to customers. Moreover, the 10% threshold under-identifies important customers because for firms with multiple production lines, it is possible that the sales from one production lines is less than 10% of the total sales of the firm, and if there is only one customer purchasing all products from this production line, this customer is certain critical to the production line and the firm, but it will not be reported.

2.4. Stochastic Actor-Oriented Models

2.4.1 Introduction to Stochastic Actor-Oriented Models

Stochastic actor-oriented models are a class of continuous-time Markov chain network models developed by sociometrists in recent decades (Snijders 2001, 2005; Snijders, Steglich, and Schweinberger, 2007; Snijders, 2017). SAOMs are designed to investigate relationship and behavior changes in one or more types of networks over time, where effects at actor, relationship, and network structure levels are explicitly modeled. In a SAOM, networks are observed at discrete time points. The model assumes that there is a sequence of unobserved opportunities to change, called micro-steps (Steglich et al., 2010), between consecutive time points. At each micro-step, an actor is randomly chosen to take exactly one action. The actor can create a new relationship, destroy an existing relationship, or do nothing. Each actor has a utility function with two components: evaluation functions and a random term. An evaluation function reflects the degree of satisfaction of the actor given his "status" in each network, where the "status" reflects the network effects at actor, dyadic, and structural levels as well as the effects of actor's characteristics outside the networks. Each effect joins the objective function linearly. The random term is assumed to have a Type I Extreme distribution (Luce & Suppes, 1965; McFadden, 1973).

In the case of this paper, let B= {1, …, 195} denotes the set of banks, and let F= {1, …, 857} denotes the set of firms. The bank lending network observed at a given time point can be represented by a 857*195 adjacency matrix, L(t), with entry l_{ij}, where $i \in F$, and $j \in B$. $l_{ij}=1$ if there is a lending relationship, and $l_{ij}=0$ otherwise. The supply chain network observed at a given time point can be represented by an 857*857 adjacency matrix, S(t), with entry s_{ij}, where $i, j \in F$. s_{ij}=1 if firm i supplies to firm j, and s_{ij}=0 otherwise. t∈ {1, 2, 3, 4, 5} denotes the five time points the networks are observed. The waiting time for an actor to be chosen to make a choice at a micro-step in network L and S follows exponential distributions with rate parameters λ^L(L(t), S(t)) and λ^S(L, S), respectively. The transition matrix of the process contains the probabilities of all possible changes, conditioning on that an actor is chosen to make a change. These probabilities follow a multinomial logit model. When it comes to actor i's turn to make a change, the probability that an actor i changes l_{ij}, to 1- l_{ij} in the bank lending network, is:

$$\mathrm{P}\left(\mathrm{i\ change\ L_{ij}} \middle| \mathrm{L(t), S(t), i\ chosen}\right) = \frac{\exp\left(\mathrm{f_i}\left(\mathrm{L^{ij}(t), S(t)}\right)\right)}{\sum_{\mathrm{h \in B}} \exp\left(\mathrm{f_i}\left(\mathrm{L^{ih}(t), S(t)}\right)\right)} \qquad (1)$$

Where $\mathrm{L^{ij}}$ denotes the adjacency matrix for the bank lending network after the tie l_{ij} is changed.

Similarly, the probability that an actor i changes s_{ij} to 1-$\mathrm{s_{ij}}$ is:

$$\mathrm{P}\left(\mathrm{i\ change\ S_{ij}} \middle| \mathrm{L(t), S(t), i\ chosen}\right) = \frac{\exp\left(g_{\mathrm{i}}\left(\mathrm{L(t), S^{ij}(t)}\right)\right)}{\sum_{\mathrm{h \in F}} \exp\left(g_{\mathrm{i}}\left(\mathrm{L(t), S^{ih}(t)}\right)\right)} \qquad (2)$$

Where $\mathrm{S^{ij}}$ denotes the adjacency matrix for the supply chain network after the tie s_{ij} is changed.

The functions $\mathrm{f_i}\left(\mathrm{L^{ij}(t), S(t)}\right)$ and $g_{\mathrm{i}}(\mathrm{L(t), S^{ij}(t)})$ are the evaluation functions of actor i in networks L(t) and S(t), respectively. Although an evaluation function may take different function form, it is typical to define it as linear combination of network statistics and their parameters:

$$\mathrm{f_i}\left(\mathrm{L^{ij}(t), S(t)}\right) = \sum_m \partial_m c_m(\mathrm{L^{ij}(t), S(t)})$$

(3)

$$g_{\mathrm{i}}(\mathrm{L(t)}, \mathrm{S^{ij}(t)}) \; = \sum_n \beta_n c_n(\mathrm{L(t)}, \mathrm{S^{ij}(t)})$$

(4)

Where $c_k(\cdot)$ represents network effects which can be actor and counterparty characteristics, dyadic characteristics, triadic and network configurations.

When it comes to an actor's time to take an action, the actor evaluates and compares the outcomes of all possible choices and chooses the option yielding the highest utility similar to the random utility theory (Train, 2009). The model is implemented as a stochastic simulation model where Monte Carlo Markov Chain implementation of the method of moments is used for parameter estimation. The goodness-of-fit of an SAOM is assessed by how well the model reproduce key characteristics of the observed networks, and the two most important characteristics are indegree distribution and outdegree distribution of each observed network. Lospinoso and Snijders (2019) propose to use a Mahalanobis distance–based Monte Carlo goodness of fit testing procedure. More details and technical notes can be found in Snijders (2001, 2005) and Snijders et al. (2007).

In the context of this paper, the closure effect can form in two ways: a firm can borrow from its supplier's bank or its customers' bank. Multilevel supplier closure refers to the tendency that a lending relationship between a borrower and a bank is more likely when the firm's customer already has a lending relationship with the bank. Similarly, Multilevel customer closure refers to the tendency that a lending relationship between a borrower and a bank is more likely when the firm's supplier already has a lending relationship with the closure bank. It is called multilevel closure because the closure effect involves two types of relations. Their mathematical are as the following:

multilevel customer closure: $\sum_{\mathrm{j} \neq \mathrm{i}} \mathrm{s_{ij} l_{hj} l_{hi}}$ (5)

multilevel supplier closure: $\sum_{j \neq i} s_{ji} l_{hj} l_{ih}$ (6)

Where $i, j \in F, and\ h \in B$. A simple example of multilevel customer closure is given in Panel A figure 2.1, and a simple example of multilevel supplier closure is given in Panel B figure 2.1. Figure 2.2 gives an example of multilevel customer closure. Solid lines indicate existing relationships, and dash lines are new relationships. j_1 and j_2 are two suppliers of the focal firm, i. h_1, h_2, h_3, and h_4 are four banks. j_1 has two existing banking relationships with h_1 and h_2, respectively, and j_2 has one existing banking relationship with h_3, and i has one existing banking relationship with h_4. Before the two new banking relationships come to exist, there is no closure at all because no bank lends to two firms. After the two new banking relationships, there are two multilevel customer closure formed, namely (i, j_1, h_2) and (i, j_2, h_3). The two new banking relationships can be a result of a syndicate loan or two separate loans. The current model does not distinguish these two possibilities.

Multilevel supplier closure is structurally opposite to multilevel customer closure because in the case of multilevel supplier closure, ties are sent from focal firms to their supply chain partners, indicating the focal firms are suppliers whereas ties are sent from the supply chain partners of focal firms to the focal firms, indicating the focal firms are customers, while the ties from focal and closure firms to banks are not affected. In other words, these two effects are negatively perfectly correlated with each other. Therefore, I have to estimate two separate SAOMs, each including one type of closure at a time, to estimate their effects.

2.4.2 SAOM Results

Table 2.3 displays the results of SAOMs. I estimate the supplier closure effect and customer closure effect separately. Columns (1) and (2) report the estimates and standard errors of multilevel supplier closure, respectively. Columns (3) and (4) report the estimates and standard errors of multilevel customer closure, respectively. The coefficients of both types of multilevel closure are positive and significant at 5% level, suggesting multilevel closure is an important mechanism driving the evolution of banking relationships. Specifically, borrowers and banks are more likely to connect with each other when the banks also lend to supply chain partners, suppliers or customers, of the borrowers.

One might be concerned that the effect of multilevel closure is superficial and coincidental. For example, banks may prefer to lend to firms that are in the upstream or downstream industries of their existing borrowers. So, it would be a pure coincidence that a new borrower is a customer or supplier of their existing borrowers. If this is the case, I should observe that banks prefer to lend to the upstream and downstream industries of the industries they specialize in. I define a bank's specialized industry as the industry that a bank makes the most loans in each year at the two-digit North American industry classification system codes (NAICS codes) level. If a bank does not make any loan in a given year, I assume that the specialized industry is the same as the previous year. Then, I compare the two-digit NAICS codes of borrowers with the specialized industries of all banks in the bank lending network using the input-output table from the website of Bureau of Economic Analysis[6]. If a pair of borrower and bank are in the same industry in a given year, then the corresponding value in the SameInd matrix of that year equals to one, and zero otherwise. If a borrower is from a downstream industry of a bank's specialized industry in a given year, then the corresponding value in the DownInd matrix of that year equals to one, and zero otherwise. UpInd matrices are defined similarly. I find that the

[6] https://www.bea.gov/industry/input-output-accounts-data

coefficient of SameInd is positive and significant, whereas the coefficients of DownInd and UpInd are negative and significant. A banking relationship is more likely to arise or extend if a borrower is from a bank's specialized industry. Nonetheless, a banking relationship is less likely if a borrower is from the downstream or upstream industry that a bank specializes in, whereas the base case is that a firm is from an industry that is unrelated to a bank's specialized industry. These results show that the multilevel closure is not a result of banks' industry preference. Otherwise, I should observe positive and significant coefficients of DownInd and UpInd.

Another concern would be that banks tend to lend to the same set of borrowers because, for example, these borrowers are creditworthy or have substantial credit demand. Multilevel closure is formed by chance as some of these borrowers are supply chain partners. This effect is captured by 4-cycle, and if it is the case, the coefficients of 4-cycle should be positive and significant in both models. However, I observe the contrary: the negative and significant coefficients indicate that a bank avoids lend to borrowers that borrow from another bank. Therefore, this 4-cycle effect should prevent, not foster, multilevel closure because when a firm and its supply chain partner borrow from the same bank, other banks would circumvent from lending to these two firms. Other effects in the SAOMs are included as basic structural controls for network evolution following the literature (e.g., Amati, Lomi, Mascia, and Pallotti, 2021). Please refer to Table A1 in Appendix for the mathematical expressions and meanings of other effects in the SOAM objective function.

The goodness-of-fit (GOF) of the SAOMs is evaluated following Lospinoso and Snijders (2019). I simulate 5,000 co-evolution trajectories and compute the value of statistics for indegree and outdegree for each trajectory. Then I compare the statistics of observed networks and simulated networks using violin graphs shown in Figure 2.3. Panel A of Figure 2.3 displays the violin graphs of the indegree and outdegree distributions of both the bank lending networks and the supply chain networks where multilevel supplier closure is estimated, and Panel B of Figure 2.3 displays the violin graphs for the same network statistics where multilevel customer closure is estimated. At each degree values, a box plot and the lines around it is called a "violin", which depicts the distribution of simulated statistics, the red dots are observed statistics, the black dots are the average values of simulated statistics, and the crosses represent outliers. If the SAOMs well describe the data, then visually, I should expect that the violins capture the statistics of observed networks I also test the hypothesis: whether the observed statistics and the simulated statistics are statistically different, and the p-value is displayed at the bottom of each violin graph. A p-value above 0.05 indicates no significant difference. All the p-values in Figure 2.3 are above 0.05, suggesting that the models fairly replicate the data.

2.5. Loan Term Implications of Multilevel Closure

In section 2.4, I find the existence of multilevel closure at the bank lending networks, which means that borrowers are more likely to establish bank-borrower relationships with banks of their supply chain partners. In this section, I take a step further and examine the economic consequences of bank-borrower relationships originated in this fashion, specifically in terms of loan terms of syndicated loans. Table 4 reports the ordinary least square analysis on the implications to loan terms of multilevel closure. Panel A reports the results of measuring multilevel closure with the dummy variable, Closure. Closure equals one if at least one bank in a loan syndicate of a borrower also lends to the borrower's supply chain partners in the past three years before activation of the syndicate loan.

Columns (1)-(5) report the results for credit lines, and columns (6)-(10) report the results for term loans. Conditional on borrower characteristics, bank characteristics, loan type, and time, I find that forming closure does not the treatment of borrowers in terms of loan spread, credit availability, and maturity, even worse, it puts borrowers under tighter constraints as the coefficients are positive and significant in the regressions of the number of financial covenants and collateral requirement for both credit lines and term loans.

It may first appear that forming closure only makes loan terms worse, however, when the roles of banks in loan syndicates are distinguished, the message becomes much clearer. I use two different dummy variables, ClosureLead and ClosureParti, to measure closure formed with lead banks and participant banks, respectively. The results are displayed in Panel B, Table 4. The left panel shows the results for loan terms of credit lines, and the right panel shows the results for term loans. I run analysis on the separate samples because they are two different products: credit lines rely on soft information banks gather in bank-borrower relationships whereas term loans are made using hard information (Berger and Udell, 1995 and 2005). I find that the effects of lead closure banks are dramatically opposite to the effects of participant banks for both types of syndicated loans. In particular, borrowers become worse off due to the presence of lead closure banks in loan syndicates. For both credit lines and term loans, they get smaller loans with higher spreads, shorter maturity, and higher chance to receive collateral requirements. In contrast, when there is at least one closure participant bank in loan syndicates, the loan terms become considerably better—the borrowers get larger loans with lower spread, longer maturity, and lower chance for collateral requirements although there will be more financial covenants.

These results for spreads, amounts, and maturity are also economically significant. For example, in terms of credit lines, when a borrower has a closure lead bank, it pays 14.54 base points (bps) more on its loans on average, which is around 7% more expensive compared with the average loan spread (195.85bps). Moreover, the size of loan decreases by around 13.7% (=exp(0.128)-1), and the maturity decreases by around 7.5% =(exp(0.073)-1) on average. In contrast, when at least one closure participant bank, the spread of this loan syndicate is expected to drop -17.35bps, almost a 10% discount, the size increases by 40% (=exp(0.331)-1), and the maturity increases by 13% (=exp(0.122)-1) on average, which is substantial. On the other hands, the number of financial covenants is increased by 0.23, which is economically insignificant. The economic significance of the results for term loans is consistent with those for credit lines, and notably, when participant banks present in loan syndicates, the discount in terms loans spreads are more than two times larger than credit lines' spreads. This difference is also statistically significant with a t-stat of 3.89 ($= \frac{-17.35-(-42.77)}{\sqrt{\left(\frac{-17.35}{-5.49}\right)^2+\left(\frac{-42.77}{-5.28}\right)^2}}$), Clogg, Petkova, and Haritou, 1995). It is expected because lenders for credit lines already have substantial amount of soft information about the borrowers, so they are not as sensitive to additional private information as term loan lenders who use mostly hard information.

In Table 1.5, I use the count of closure participant banks in a loan syndicate as an alternative measure. Since syndicated loans have only one lead banks, the count for lead closure banks coincides with the dummy variable used in Table 4. I run the same regressions in Panel A as in Panel B, Table 4, and in Panel B, I control for the number of banks in a loan syndicate and the interaction between the count of closure participant banks to account for the possibility that a loan syndicate increases the number of banks to accommodate for more closure banks. I also run regressions using closure measures calculated over a five-year time horizon (ClosureLead5y, ClosureOther5y, and CountClosureParti5y) as a robustness check. Results are shown in Table A2. The results in both Table 1.5 and Table A2 are highly consistent with Table 4, suggesting that the results are robust.

To sum up, I find evidence suggesting that borrowers do not get better but only more expensive loans when the lead banks in their syndicates also lend to their supply chain partners. In the meanwhile, they do get lower spreads and larger amount if the participant banks are also closure banks with almost negligible increases in covenants and collateral requirement. These results are rather surprising because, in the existing literature concerning syndicated loans, participant banks do not play a significant role in determining loan terms (e.g., Sufi, 2007; Ivashina, 2009). However, I find evidence that in the case of multilevel closure, closure participant banks are the banks sweetening loan terms whereas closure lead banks do the opposite. This is consistent with the market flex model (Zhang, Zhang, and Zhao, 2022). They argue that a lead bank intentionally underprices the loan it syndicates in order to incentivize participant banks to reveal their own private information, in turn, the release of private information, especially the information turn out to be good signals, reduces underpricing. In the context of this paper, although it is possible that lead closure banks may have private information, they cannot possibly know all information relating to their borrowers in the supply chain network. As a result, inviting banks lend to both the borrowers and the supply chain partners of the borrowers to participate would be optimal because those banks can acquire private information of the borrowers from their supply chain partners. The negative relation between loan spreads and the number of closure participant banks displayed in Columns (1) and (6) in both panels of Table 4 is consistent with their predictions. Moreover, the significant coefficients of the main independent variables in Table 2.5 indicate that the relations between loan terms with lead closure banks and participant closure banks are significant on the intensive margins, as well. This means that the effects of participant banks increase as the number increases, which is consistent with the market flex model. In addition, the effects of lead closure banks almost cancel out the effects of borrowers' relationship intensity with their lead banks for both credit lines and term loans. This may help to explain the unresolved debate between the dark side and the bright side of bank relationships because most of the research in this area does not account for the effect of lead closure banks, so if their samples are dominated by firms with lead closure banks, they might observe insignificant or even negative relations between loan terms and relationship intensity.

2.6. Identification Concerns

In this section, I address identification concerns. There are three potential concerns, namely, reverse causality bias, omitted variable bias, and selection bias. Specifically, to this paper, reverse causality bias is unlikely because it is almost impossible that certain loan terms lead to the formation of multilevel closure. In other words, it is implausible that a group of firms and banks decide to establish and maintain relationships so that a firm can get a cheaper and larger syndicated loan. Moreover, the omitted variable bias is partially addressed since I not only have a lot of control variables of the borrowers and lead banks, but also, I saturate the models with borrower fixed effects, lead bank fixed effects, and year fixed effects which can absorb borrower, lead bank, and time invariant unobservable variables. However, I do recognize that a lot of information of participant banks, supply-chain relationships, and the banking relationships between closure firms and closure banks are lost. Ideally, I want to control the relationship strength between borrowers and their supply chain partners, typically measured by sales between two firms. However, this variable contains too many missing values in Compustat historical segment, making it impossible to use. On the other hand, due to the limitation of ordinary least square regressions, there is no efficient way to account for the characteristics of each relationship or counterparty involved in a closure.

In the remaining of this section, I will focus on addressing potential selection bias. In this paper, selection bias can take two forms: first, firms which can form closure, in other words, borrow from their supply chain partners' banks, may be systematically different from those cannot. I handle this concern using propensity score matching (PSM). Second, banks who have strong influence over loan terms self-select to participate in loan syndications. I cope with this concern using Heckman selection model. I am not concerned with the potential selection bias for lead closure banks as their effects are weak and limited.

Table 2.6 displays the results of OLS analysis run on the subsample matched using PSM. The treated variable is a dummy variable equals to one if there exists at least one closure participant bank in a given loan syndicate and equals to zero otherwise. I match treated borrowers with five untreated borrowers with similar observed borrower characteristics on the common support. The coefficients of both the number of closure participant banks and closure lead banks are significant and highly consistent with those in Panel A, Table 25, suggesting that the results are not driven by systematic differences between firms which have closure participant banks in their loan syndicates from those do not.

I use a two-step Heckman selection procedure to address the concern that the banks of borrowers' supply chain partners with substantial influence over loan terms self-select themselves to participate in the borrowers' loan syndications. The results are presented in Table 2.7. Columns (1) and (7) show the results of the first stage regression for credit lines and term loans, respectively. In the first stage, I estimate the probability of at least one closure participant bank presenting in a loan syndicate. Columns (2)-(6) and (8)-(12) illustrate the second stage results. The coefficients of the key independent variables are highly consistent with the main results. Moreover, the inverse mills ratios are insignificant in all second stage regressions, suggesting that selection bias is not a major concern to the empirical study.

2.7. Conclusion

In this paper, I address two important overlooked questions from the bank-borrower relationship literature: What are the origins of bank-borrower relationships, and do these origins influence the treatment of relationship borrowers? With regard to the question of origin, I use SAOM to model endogenous co-evolution of bank-borrower relationships and supply-chain relationships. The results suggest that supply-chain relationships in some cases yield new bank-borrower relationships. I specifically find that supply-chain network connections of firms result in multilevel closures that create bank-borrower relationships for these firms with the banks of their suppliers or customers, controlling for other network effects.

For borrower treatment, the findings vary with the lending roles of the banks in the relationships. When the closure banks directly underwrite the loans, borrowers tend to pay unfavorably higher interest rate spreads, while closure with participant banks in loan syndicates generally leads to more favorable spreads that are lower, loan amounts that are larger, and maturities that are longer. Although the relationship banking literature focuses on the main underwriting banks, my findings that relationships with participant banks significantly affect borrower treatment may add to the bank-borrower relationship literature that typically considers only relationships with underwriting banks. They may use their private information to win over better loan terms for the borrowers, perhaps to secure future business with the borrowers, consistent with the market flex model (Zhang, Zhang, and Zhao, 2022).

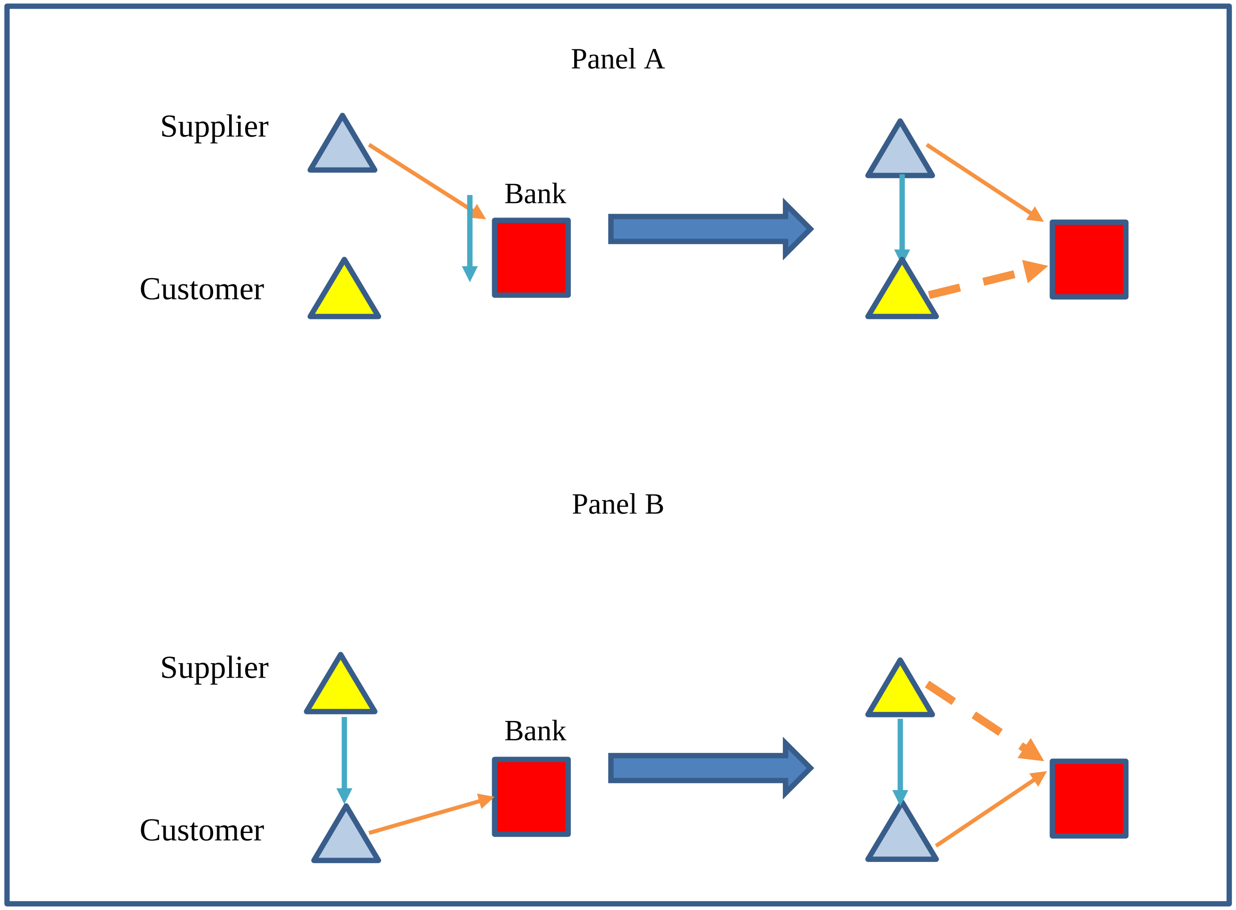


Figure 2.1 Customer and Supplier Closure Effects

In this figure, yellow triangles represent focal firms. Blue triangles represent the supply chain partners of focal firms. Red squares represent banks. Green lines represent banking relationships, blue lines represent supplying relationships. solid lines are preexisting relationships, and dash lines are newly formed relationships. Panel A shows a simple example of multilevel customer closure. Panel B shows a simple example of multilevel supplier closure.

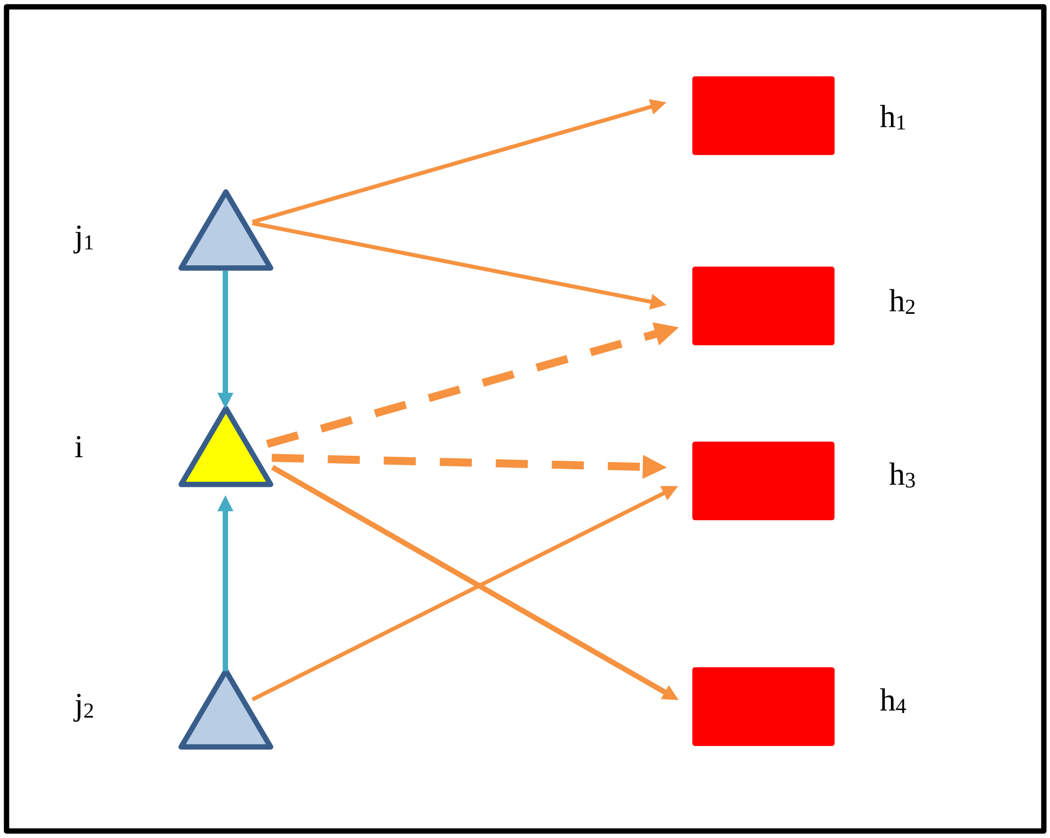
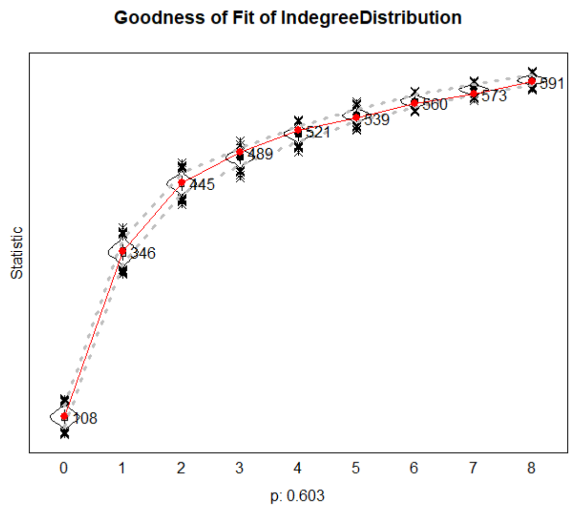


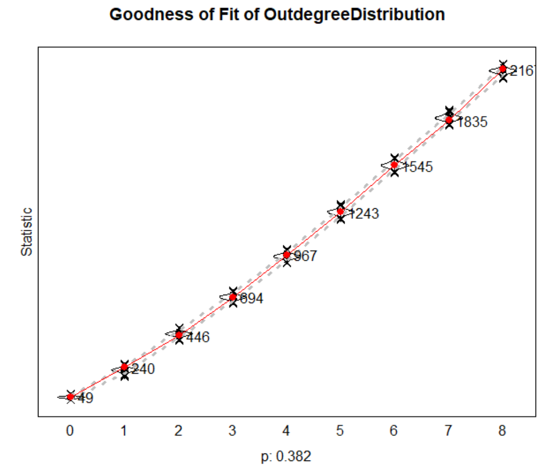
Figure 2.2 Closure Effect in Networks.

In this figure, yellow triangles represent focal firms. Blue triangles represent the supply chain partners of focal firms. Red squares represent banks. Green lines represent banking relationships, blue lines represent supplying relationships. solid lines are preexisting relationships, and dash lines are newly formed relationships.

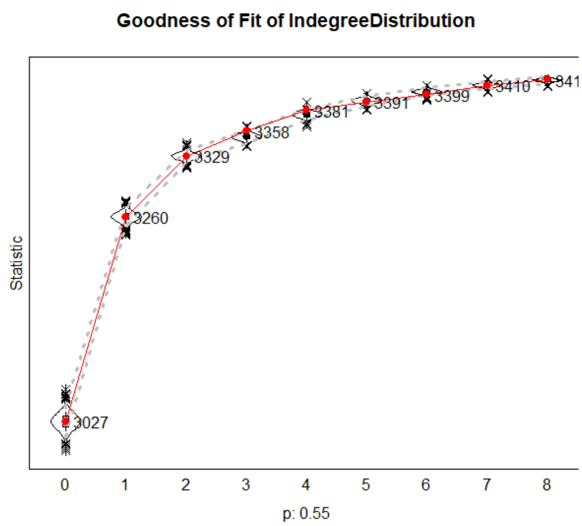
Panel A



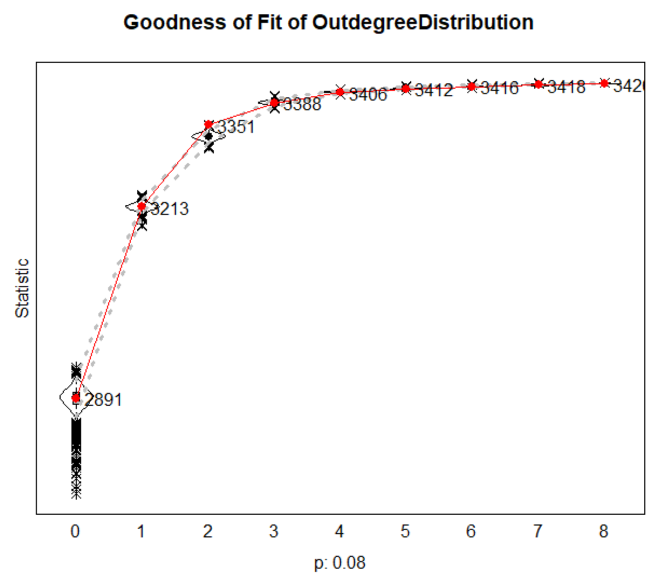
A1: Multilevel Supplier Closure, Bank Lending Networks



A2: Multilevel Supplier Closure, Bank Lending Networks

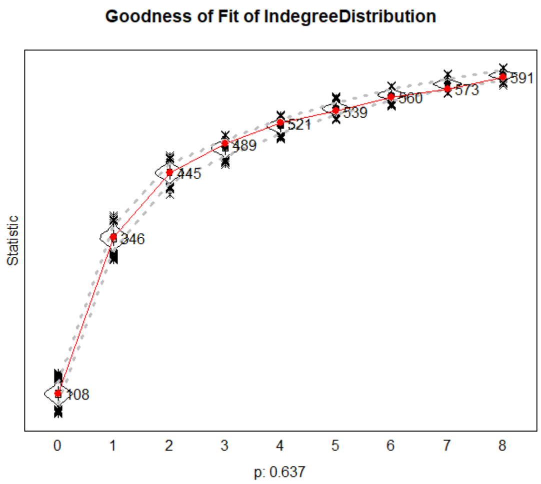


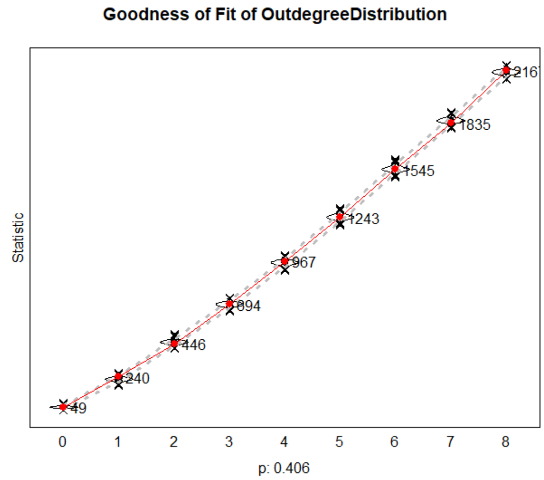
A3: Multilevel Supplier Closure, Supply Chain Networks



A4: Multilevel Supplier Closure, Supply Chain Networks

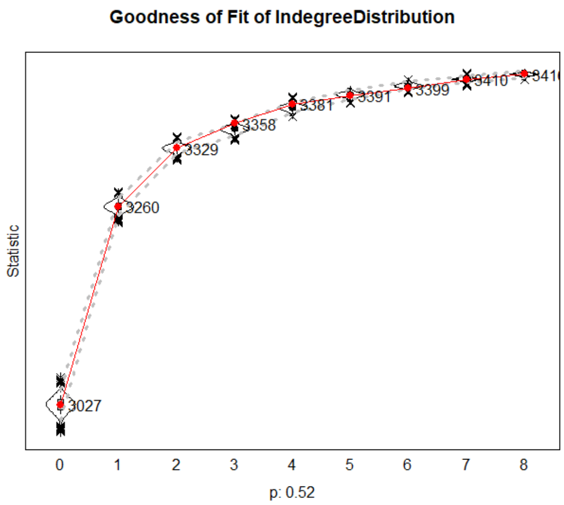
Panel B

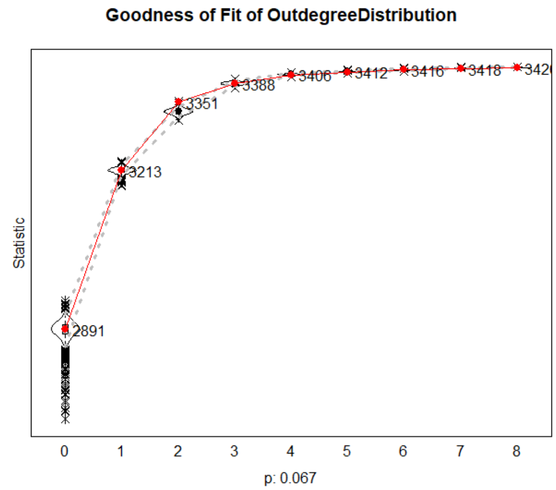




B1: Multilevel Customer Closure, Bank Lending Networks

B2: Multilevel Customer Closure, Bank Lending Networks





B3: Multilevel Customer Closure, Supply Chain Networks

B4: Multilevel Customer Closure, Supply Chain Networks

Figure 2.3 Violin Charts for SOAM

Figure 2.3 shows the goodness-of-fit results (violin graph) for the co-evolution of the bank lending networks and supply chain networks using stochastic actor-oriented models. The p-value for the hypothesis test for whether the observed and simulated statistics are different is presented at the bottom of each figure. Panel A shows the results using multilevel supplier closure as the main effect, and Panel B shows the results using multilevel customer closure as the main effect. Figure A1 shows the indegree (the number of borrowers) distribution of the bank lending networks. Figure A2 shows the outdegree (the number of banks of a borrower) distribution of the bank lending networks. Figure A3 shows the indegree (the number of suppliers) distribution of the supply chain networks. Figure A4 shows the outdegree (the number of customers) distribution of the supply chain networks. The organization of figures in Panel B follows the same pattern as Panel A.

Table 2.1: Variable Definitions and Summary Statistics

This table displays variable definitions and summary statistics. Panel A displays the definitions and summary statistics of loan level variables, including loan terms, which are also the main dependent variables in the empirical analysis, the main variables, measures of closure, and relationship intensity (RelIntensity) between borrowers and the lead banks following Bharath, Dahiya, Saunders, and Srinivasan (2007). Panel B displays the definitions and summary statistics of firm variables. Panel C displays the definitions and summary statistics of bank variables. I aggregate the bank level data to the ultimate parent level, to be consistent with the paper, I refer these variables as "bank variables". The sample period is 2001 to 2020. All variables except for dummy variables and count variables are winsorized at 1% and 99%.

Panel A: Loan Terms

Variable	Definition	Count	Mean	Std	Q1	Median	Q3
Spread (bps)	The loan spread is the all-in spread drawn in the DealScan database. All-in spread drawn is defined as the amount the borrower pays in basis points over LIBOR or the LIBOR equivalent for each dollar drawn down. For loans not based on LIBOR, LPC converts the spread into LIBOR terms by adding or subtracting a differential that is adjusted periodically. This measure adds the borrowing spread of the loan over LIBOR with any annual fee paid to the bank group.	12,534	195.85	142.32	105	162.5	250
Amount (million $)	Size of a loan, measured in millions of dollars.	12,534	1,861.17	4,726.62	250	725	1,865
Maturity (Months)	Maturity is measured in months.	12,444	48.84	20.92	36	60	60
#Covenant	The number of financial covenants, ranged from 0-6.	12,534	1.13	1.22	0	1	2
Collateral	A dummy variable equals to one if a loan is secured by collateral and zero otherwise.	12,534	0.46	0.50	0	0	1

Closure	A dummy variable equals to one if at least one bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise.	12,534	0.73	0.44	0	1	1
ClosureLead	A dummy variable equals to one if the lead bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise.	12,534	0.61	0.49	0	1	1
ClosureParti	A dummy variable equals to one if at least one participant banks in a loan syndicate also lend to the supply chain partners of the borrower, zero otherwise.	12,534	0.61	0.49	0	1	1
CountClosureParti	The number of participant banks in a loan syndicate that also lend to the supply chain partners of the borrower in the past three years.	12,534	2.20	2.80	0	1	3
RelIntensity	The ratio of the amount of loans borrowed by a firm from a bank in the past three years to the amount of loans borrowed by the firm from the entire bank loan market in the past three years.	12,534	0.56	0.46	0	0.83	1.00

Panel B: Borrower Variables

Variable	Definition	Count	Mean	Std	Q1	Median	Q3
BorrowerSize ($B)	The natural log of the book value of total assets of the borrower in millions of dollars.	6,771	3.10	6.82	0.87	3.23	12.33
BorrowerROA	The ratio of net income to total assets.	6,771	0.02	0.21	0.01	0.04	0.08
BorrowerBook Leverage	The ratio of the book value of total debt to the book value of assets. Total Debt / (Total Debt	6,771	0.30	0.23	0.15	0.28	0.41

	+ Market Value of Equity), where Total Debt = Long-Term Debt + Total Debt in Current Liabilities.						
BorrowerTangibility	The ratio of tangible assets (PPENT) to total assets	6,771	0.33	0.26	0.12	0.25	0.52
BorrowerCash Holding	The ratio of Cash and marketable securities to total assets.	6,771	0.10	0.12	0.02	0.06	0.14

Panel C: Bank Variables

Variable	Definition	Count	Mean	Std	Q1	Median	Q3
BankSize ($B)	The natural log of gross total assets[11] (GTA) of the bank.	474	1,176.75	703.67	594.83	1,336.31	1,719.94
BankCapitalRatio	The ratio of equity capital to GTA.	474	0.11	0.04	0.09	0.10	0.12
BankROA	The ratio of net income to GTA.	474	0.01	0.01	0.01	0.01	0.01
TotalLoan	The ratio of total loans to GTA.	474	0.56	0.17	0.46	0.61	0.69
Liquidity	The ratio of cash to total deposits.	474	0.12	0.13	0.05	0.07	0.13
Efficiency	The ratio of total expenses to GTA.	474	0.04	0.01	0.03	0.04	0.05
MarketSensitivity	The ratio of the difference between short-term assets and short-term liabilities to GTA.	474	-0.37	0.22	-0.52	-0.42	-0.27
NPL	The ratio of non-performing loans to total loans.	474	0.02	0.02	0.01	0.01	0.02

[11] Gross total assets equals to the sum of total assets, the allowance for loan and lease losses, and the allocated transfer risk reserve.

Table 2.2: Network Summary Statistics

This table shows the descriptive statistics of the bank lending networks and the supply chain networks from 2015-2019. Density is a ratio of the number of observed ties to the number of possible ties. Distance is a measure of clustering, which is calculated as the average number of edges between any two actors in a network that are possible to be connected. Jaccard is a similarity measure. It compares networks in the previous period and the current period. Panel A displays the indegree and outdegree distributions of the bank lending networks, where the indegree and outdegree in the context of this paper means the number of borrowers and the number of borrowers' banks. Panel C displays the indegree and outdegree distributions of the supply chain networks, where the indegree and outdegree in the context of this paper means the number of suppliers of firms and the number of customers of firms in the networks. Panel B and C shows the summary statistics for tie changes in the bank lending networks and supply chain networks. Specifically, 0=>0 means that unconnected actors in the previous period remains unconnected in the current period. 0=>1 means unconnected actors in the previous periods become connected in the current period. 1=>0 means that connected actors in the previous period become unconnected in the current period. 1=>1 means that connected actors in the previous period remain connected in the current period. I show minimum and maximum because the supply chain networks are very sparse, so Q1, median and Q3 are all zeros.

Panel A: Bank Lending Networks

		Indegree: The Number of Borrowers						**Outdegree: The Number of Banks**					
Year	**Density**	**n**	**mean**	**std**	**Q1**	**median**	**Q3**	**n**	**mean**	**std**	**Q1**	**median**	**Q3**
2015	0.010	195	8.09	4.12	5	8	11	857	6.48	4.46	3	6	9
2016	0.010	195	8.21	4.30	6	8	10	857	6.72	4.56	3	6	9
2017	0.011	195	8.87	4.21	6	9	11	857	7.37	4.54	4	7	10
2018	0.012	195	9.39	3.79	7	9	12	857	7.87	4.53	5	8	11
2019	0.012	195	9.44	3.89	7	9	12	857	7.94	4.43	5	8	11

Panel B: Bank Lending Networks Tie Changes Over Time

Periods	0 => 0	0 =>1	1 =>0	1 =>1	Distance	Jaccard
2015=>2016	733,302	38	36	216	74	0.76
2016=>2017	733,299	39	45	209	84	0.71
2017=>2018	733,310	34	40	208	74	0.74
2018=>2019	733,314	36	50	192	86	0.69

Panel C: Supply Chain Networks

		Indegree: Number of Suppliers					Outdegree: Number of Customers				
Year	**Density**	**n**	**mean**	**std**	**min**	**max**	**n**	**mean**	**std**	**min**	**max**
2015	0.0003	857	0.29	1.48	0	31	857	0.29	0.91	0	12
2016	0.0003	857	0.30	1.48	0	33	857	0.30	0.92	0	13
2017	0.0003	857	0.29	1.47	0	32	857	0.29	0.92	0	14
2018	0.0003	857	0.28	1.37	0	29	857	0.28	1.06	0	19
2019	0.0003	857	0.27	1.30	0	27	857	0.27	1.01	0	19

Panel D: Supply Chain Networks Tie Changes Over Time

Periods	0 => 0	0 =>1	1 =>0	1 =>1	Distance	Jaccard
2015=>2016	160,995	565	365	5,190	930	0.85
2016=>2017	160,471	889	330	5,425	1,219	0.82
2017=>2018	159,940	861	429	5,885	1,290	0.82
2018=>2019	159,790	579	520	6,226	1,099	0.85

Table 2.3: Estimation Results of Stochastic Actor-Oriented Models

This table shows the estimation results of the co-evolution of the bank lending networks and the supply chain networks using stochastic actor-oriented models. Panel A shows the estimates and standard errors of the effects in the bank lending networks, and Panel B shows the estimates and standard errors of the effects in the supply chain networks. Columns (1) and (2) in each Panel shows the results using multilevel supplier closure as the main effect, and Columns (3) and (4) in each Panel shows the results using multilevel customer closure as the main effect. Please see Table A1 in Appendix for details of other effects in this table. The sample period is 2015-2019. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Bank Lending Network

	Multilevel Supplier Closure		**Multilevel Customer Closure**	
Effect Name	**(1) Estimate**	**(2) Standard Error**	**(3) Estimate**	**(4) Standard Error**
Multilevel Closure	0.1727**	0.0816	0.1663**	0.0767
UpInd	-0.1888***	0.0467	-0.1909***	0.0467
DownInd	-0.0636	0.0524	-0.0646	0.0518
SameInd	0.2466***	0.0601	0.2488***	0.0597
4-cycle	-0.0012***	0.0001	-0.0012***	0.0001
Indegree - Popularity	-0.0061***	0.0004	-0.0061***	0.0004
Indegree - Popularity (sqrt)	0.3135***	0.0126	0.3128***	0.0124
Out-Isolate	2.6516***	0.6491	2.6659***	0.6328
Anti In-Isolates	-0.1481	0.1243	-0.1461	0.1249
Anti In-Near-Isolates	-0.9637***	0.1174	-0.9627***	0.1178
Indegree at Least 3	-0.7564***	0.1594	-0.7524***	0.1579
Out-In Degree Assortativity	0.0652***	0.0044	0.0657***	0.0044
LenderROA	-2.3342**	0.9344	-2.3416**	0.9628
LenderCapitalRatio	-1.0217***	0.1558	-1.0198***	0.1531
LenderLogGTA	-0.2449***	0.0109	-0.2453***	0.0109
FirmAT	-0.0931***	0.0146	-0.0899***	0.0145
Same Size Borrower	-3.4751***	0.8082	-3.46***	0.8379
FirmBookLeverage Ego	0.0443	0.0988	0.0366	0.0950
Same BookeLeverage Borrower	0.0895***	0.0308	0.0903***	0.0301
FirmROA Ego	-0.0881	0.1218	-0.0857	0.1159
Same ROA Borrower	-2.3474***	0.7790	-2.3743***	0.8014
Borrower Selling Activity in Supply Chain Networks	-0.0293	0.0389	-0.1329**	0.0620
Borrower Purchasing Activity in Supply Chain Networks	-0.2029***	0.0665	-0.0855**	0.0391

Panel B: Supply Chain Network

	Multilevel Supplier Closure		Multilevel Customer Closure	
Effect Name	**(1) Estimate**	**(2) Standard Error**	**(3) Estimate**	**(4) Standard Error**
GWESP Two-Out-Star	1.9716	1.2030	1.9552*	0.9996
Indegree - Popularity	0.1721	0.2868	0.1773	0.2147
Indegree - Popularity (sqrt)	0.1745	2.9067	0.0886	2.2265
Outdegree - Popularity	-2.696	3.4412	-2.6735	2.8777
Outdegree - Popularity (sqrt)	3.484	4.3686	3.4565	3.6350
Out-Isolate	7.9905***	2.1314	7.9042***	1.6487
Anti In-Isolates	-2.4107***	0.5614	-2.4388***	0.4601
Anti In-Near-Isolates	-1.6024***	0.4403	-1.6255***	0.3973
Indegree at Least 3	-1.6948***	0.4773	-1.7121***	0.4691
Out-In Degree^(1/2) Assortativity	-0.9419	0.7859	-0.9092	0.6211
FirmAT Customer	0.5881***	0.1799	0.5912***	0.1474
FirmAT Supplier	-0.0144	0.0819	-0.0146	0.0755
FirmBookLeverage Customer	-0.2584	0.6602	-0.2613	0.6441
FirmBookLeverage Supplier	-0.3824	0.4864	-0.3837	0.4766
FirmROA Customer	1.3172**	0.5923	1.323**	0.5972
FirmROA Supplier	-1.0115*	0.5549	-1.0147*	0.5654
Bank Lending Network Popularity	0.0864	0.2341	0.087	0.2096
Bank Lending Network Activity	-0.1156	0.2730	-0.1182	0.2479
Multilevel Supply Chain Closure	0.0973	0.1370	0.098	0.1121

Table 2.4: Loan Term Implications of Multilevel Closure—Ordinary Least Square Analysis

This table presents the Ordinary least square analysis results for the implications of multilevel closure to bank loan terms. Columns (1)-(5) show the results for credit lines, and Columns (6)-(10) show the results for term loans. The dependent variables in both the left and right panels are loan spread (Spread), the natural log of loan amount (Amount), the natural log of loan maturity (Maturity), the number of financial covenants (#Covenant), and collateral requirement (Collateral), respectively. In Panel A, the main independent variable is Closure, a dummy variable equals to one if at least one bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise. In Panel B, the main independent variables are ClosureLead and ClosureParti. ClosureLead is a dummy variable equals to one if the lead bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise, and ClosureParti is a dummy variable equals to one if at least one participant banks in a loan syndicate also lend to the supply chain partners of the borrower, zero otherwise. Variables in BankControls are BankSize, BankCapitalRatio, BankROA,TotalLoan, Liquidity, Efficiency, and MarketSensitivity. All regressions control for three-digit SIC industry fixed effects, lead bank fixed effects, and year fixed effects. t-statistics are reported in parentheses. The sample period is 2001-2020. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: All Bank Closure

	Credit Lines					Term Loans				
Dependent Variables:	**(1) Spread**	**(2) Amount**	**(3) Maturity**	**(4) #Covenant**	**(5) Collateral**	**(6) Spread**	**(7) Amount**	**(8) Maturity**	**(9) #Covenant**	**(10) Collateral**
Closure	0.979	0.103***	0.010	0.154***	-0.001	-10.449	0.092	0.027	0.188***	-0.022
	(0.31)	(2.91)	(0.58)	(3.64)	(-0.08)	(-1.57)	(1.42)	(0.97)	(2.71)	(-0.76)
RelIntensity	-19.861***	0.211***	-0.062***	0.153***	-0.051***	-35.784***	0.184***	-0.058**	0.272***	-0.044*
	(-7.71)	(6.67)	(-4.55)	(4.34)	(-3.62)	(-5.84)	(3.20)	(-2.28)	(4.46)	(-1.87)
BorrowerSize	-18.638***	0.497***	-0.045***	-0.213***	-0.106***	-12.220***	0.453***	-0.041***	-0.175***	-0.070***
	(-17.41)	(34.78)	(-6.60)	(-14.12)	(-17.72)	(-4.68)	(16.00)	(-3.93)	(-7.55)	(-7.24)
BorrowerROA	-350.155***	1.044***	0.494***	-0.160	-1.113***	-359.180***	0.652	0.807***	0.031	-0.595***

	(-15.75)	(5.69)	(4.55)	(-0.65)	(-11.12)	(-8.46)	(1.63)	(4.62)	(0.07)	(-3.98)
BorrowerBookLeverage	100.141***	0.502***	0.109**	0.043	0.401***	102.031***	0.243	0.283***	-0.644***	0.352***
	(11.27)	(4.59)	(2.05)	(0.34)	(8.19)	(6.21)	(1.48)	(3.99)	(-3.68)	(5.36)
BorrowerTangibility	-5.932	-0.339***	-0.081	-0.086	-0.179***	32.114	-0.389*	-0.120	-0.057	-0.134
	(-0.44)	(-2.83)	(-1.33)	(-0.55)	(-2.98)	(1.17)	(-1.86)	(-1.28)	(-0.24)	(-1.55)
BorrowerCashHolding	3.951	-1.044***	-0.108	-0.355	-0.102	43.314	-0.507	0.277**	-0.831**	-0.247
	(0.22)	(-5.91)	(-1.10)	(-1.45)	(-1.08)	(1.08)	(-1.36)	(1.98)	(-2.13)	(-1.57)
BankControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	289.854***	16.622***	4.332***	2.973***	1.378***	340.669***	17.244***	4.277***	2.898***	1.263***
	(15.01)	(66.75)	(31.73)	(10.22)	(12.48)	(7.05)	(38.62)	(23.65)	(6.11)	(7.43)
Adj.R^2	0.537	0.694	0.302	0.232	0.371	0.420	0.636	0.219	0.348	0.281
N	7191	7191	7157	7191	7191	2916	2916	2890	2916	2916

Panel B: Lead Bank Closure V.S. Participant Bank Closure

	Credit Lines					**Term Loans**				
Dependent Variables:	**(1) Spread**	**(2) Amount**	**(3) Maturity**	**(4) #Covenant**	**(5) Collateral**	**(6) Spread**	**(7) Amount**	**(8) Maturity**	**(9) #Covenant**	**(10) Collateral**

ClosureLead	14.541***	-0.128***	-0.073***	-0.012	0.035**	21.367***	-0.116*	0.009	-0.014	0.046*
	(5.36)	(-3.21)	(-3.48)	(-0.28)	(2.08)	(3.08)	(-1.86)	(0.31)	(-0.20)	(1.67)
ClosureParti	-17.351***	0.331***	0.122***	0.231***	-0.028*	-42.767***	0.329***	0.025	0.231***	-0.059**
	(-5.49)	(7.49)	(5.19)	(5.48)	(-1.74)	(-7.48)	(5.35)	(0.87)	(3.64)	(-2.30)
RelIntensity	-18.814***	0.191***	-0.069***	0.139***	-0.049***	-31.104***	0.149***	-0.060**	0.251***	-0.038
	(-7.45)	(6.12)	(-5.10)	(3.96)	(-3.50)	(-5.28)	(2.59)	(-2.35)	(4.05)	(-1.63)
BorrowerSize	-17.862***	0.482***	-0.051***	-0.223***	-0.105***	-10.683***	0.442***	-0.041***	-0.183***	-0.067***
	(-16.44)	(32.94)	(-7.31)	(-14.89)	(-17.28)	(-4.16)	(15.65)	(-4.03)	(-8.06)	(-6.97)
BorrowerROA	-343.927***	0.951***	0.453***	-0.211	-1.101***	-342.357***	0.523	0.796***	-0.065	-0.571***
	(-15.48)	(5.25)	(4.14)	(-0.86)	(-11.03)	(-8.19)	(1.32)	(4.55)	(-0.15)	(-3.84)
BorrowerBookLeverage	97.875***	0.536***	0.124**	0.061	0.397***	91.270***	0.318*	0.287***	-0.595***	0.334***
	(11.11)	(4.88)	(2.32)	(0.49)	(8.12)	(5.61)	(1.96)	(4.07)	(-3.42)	(5.12)
BorrowerTangibility	-7.327	-0.328***	-0.075	-0.086	-0.183***	30.850	-0.381*	-0.120	-0.055	-0.137
	(-0.55)	(-2.75)	(-1.21)	(-0.55)	(-3.04)	(1.14)	(-1.85)	(-1.29)	(-0.23)	(-1.56)
BorrowerCashHolding	0.159	-0.999***	-0.087	-0.339	-0.109	44.704	-0.528	0.273*	-0.850**	-0.250
	(0.01)	(-5.64)	(-0.89)	(-1.39)	(-1.15)	(1.15)	(-1.43)	(1.95)	(-2.18)	(-1.59)
BankControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

IndustryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	290.495***	16.633***	4.324***	3.010***	1.369***	328.751***	17.303***	4.288***	3.019***	1.221***
	(15.00)	(68.32)	(32.10)	(10.39)	(12.44)	(6.99)	(40.03)	(23.75)	(6.37)	(7.25)
Adj.R^2	0.542	0.700	0.308	0.236	0.372	0.438	0.643	0.219	0.350	0.283
N	7191	7191	7157	7191	7191	2916	2916	2890	2916	2916

Table 2.5: Loan Term Implications of Multilevel Closure using Alterative Measures—Ordinary Least Square Analysis

This table presents the Ordinary least square analysis results for the implications of multilevel closure to bank loan terms. Columns (1)-(5) show the results for credit lines, and Columns (6)-(10) show the results for term loans. The dependent variables in both the left and right panels are loan spread (Spread), the natural log of loan amount (Amount), the natural log of loan maturity (Maturity), the number of financial covenants (#Covenant), and collateral requirement (Collateral), respectively. In Panel A, the main independent variables are ClosureLead and CountClosureParti. Closure is a dummy variable equals to one if at least one bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise. It is the same as the count of closure lead bank. CountClosureParti is the number of participant banks in a loan syndicate that also lend to the supply chain partners of the borrower in the past three years. In Panel B, the main independent variables are Closure and CountClosureParti. In addition, I control for BankCount, the number of banks in a syndicate and the interaction of CountClosureParti and BankCount to isolate the syndicate size effect from the effect of CountClosureParti. Variables in BankControls are BankSize, BankCapitalRatio, BankROA,TotalLoan, Liquidity, Efficiency, and MarketSensitivity. All regressions control for three-digit SIC industry fixed effects, lead bank fixed effects, and year fixed effects. t-statistics are reported in parentheses.The sample period is 2001-2020. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Intensive Margin

	Credit Lines					**Term Loans**				
Dependent Variables:	**(1) Spread**	**(2) Amount**	**(3) Maturity**	**(4) #Covenant**	**(5) Collateral**	**(6) Spread**	**(7) Amount**	**(8) Maturity**	**(9) #Covenant**	**(10) Collateral**
ClosureLead	5.516**	-0.024	-0.028**	-0.057**	0.009	14.403***	-0.010	0.025	-0.051	0.042**
	(2.06)	(-0.67)	(-2.01)	(-1.98)	(0.69)	(2.96)	(-0.24)	(1.23)	(-1.35)	(2.55)
CountClosureParti	-2.947***	0.059***	0.019***	0.054***	-0.002	-9.870***	0.072***	0.003	0.085***	-0.018***
	(-5.74)	(8.71)	(5.31)	(8.00)	(-0.57)	(-9.10)	(6.19)	(0.66)	(7.87)	(-3.18)
RelIntensity	-18.942***	0.193***	-0.068***	0.136***	-0.051***	-29.440***	0.148***	-0.056**	0.227***	-0.031
	(-7.42)	(6.29)	(-5.00)	(3.88)	(-3.58)	(-4.96)	(2.60)	(-2.20)	(3.72)	(-1.36)

BorrowerSize	-17.563***	0.473***	-0.053***	-0.232***	-0.106***	-10.956***	0.438***	-0.043***	-0.191***	-0.068***
	(-15.55)	(32.61)	(-7.48)	(-15.63)	(-17.13)	(-4.22)	(15.53)	(-4.11)	(-8.40)	(-7.06)
BorrowerROA	-344.987***	0.946***	0.457***	-0.250	-1.110***	-331.413***	0.466	0.802***	-0.203	-0.542***
	(-15.58)	(5.14)	(4.18)	(-1.03)	(-11.06)	(-8.04)	(1.17)	(4.60)	(-0.49)	(-3.73)
BorrowerBookLeverage	99.614***	0.508***	0.112**	0.045	0.401***	86.308***	0.333**	0.282***	-0.521***	0.320***
	(11.24)	(4.82)	(2.13)	(0.36)	(8.19)	(5.37)	(2.03)	(3.94)	(-3.01)	(4.91)
BorrowerTangibility	-5.639	-0.356***	-0.086	-0.097	-0.180***	27.123	-0.350*	-0.118	-0.012	-0.143
	(-0.42)	(-3.03)	(-1.42)	(-0.61)	(-2.99)	(1.00)	(-1.70)	(-1.25)	(-0.05)	(-1.63)
BorrowerCashHolding	2.317	-1.039***	-0.104	-0.348	-0.103	42.230	-0.519	0.273*	-0.829**	-0.253
	(0.13)	(-5.94)	(-1.07)	(-1.44)	(-1.10)	(1.10)	(-1.42)	(1.95)	(-2.14)	(-1.63)
BankControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	286.646***	16.754***	4.361***	3.165***	1.371***	325.196***	17.341***	4.300***	3.120***	1.225***
	(14.83)	(69.35)	(32.63)	(10.98)	(12.46)	(7.06)	(40.67)	(24.02)	(6.71)	(7.32)
Adj.R^2	0.541	0.702	0.307	0.241	0.371	0.447	0.645	0.220	0.364	0.288
N	7191	7191	7157	7191	7191	2916	2916	2890	2916	2916

Panel B: Additional Controls

Dependent Variables:	Credit Lines (1) Spread	(2) Amount	(3) Maturity	(4) #Covenant	(5) Collateral	Term Loans (6) Spread	(7) Amount	(8) Maturity	(9) #Covenant	(10) Collateral
ClosureLead	2.725	0.051	-0.002	0.015	0.009	11.610***	0.017	0.032	-0.022	0.038**
	(1.06)	(1.60)	(-0.17)	(0.49)	(0.62)	(2.51)	(0.42)	(1.58)	(-0.61)	(2.26)
CountClosureParti	-5.273***	0.073***	0.036***	0.031**	-0.016**	-12.278***	0.093***	-0.003	0.069***	-0.023**
	(-4.51)	(5.11)	(4.53)	(2.06)	(-2.42)	(-5.91)	(4.05)	(-0.29)	(3.28)	(-2.07)
*BankCount	-4.494***	0.095***	0.037***	0.073***	-0.008***	-8.693***	0.081***	0.016***	0.065***	-0.015***
	(-9.03)	(14.05)	(10.60)	(10.37)	(-2.76)	(-8.99)	(7.58)	(3.98)	(6.36)	(-3.10)
CountClosureParti *BankCount	0.490***	-0.007***	-0.004***	-0.003**	0.002***	0.888***	-0.008***	-0.001	-0.004**	0.002*
	(5.40)	(-6.39)	(-5.58)	(-2.25)	(3.14)	(5.74)	(-5.22)	(-1.12)	(-2.41)	(1.78)
RelIntensity	-16.539***	0.144***	-0.087***	0.099***	-0.046***	-25.734***	0.114**	-0.062**	0.202***	-0.025
	(-6.69)	(4.84)	(-6.39)	(2.81)	(-3.26)	(-4.50)	(2.04)	(-2.45)	(3.33)	(-1.08)
BorrowerSize	-16.080***	0.443***	-0.065***	-0.252***	-0.102***	-9.294***	0.423***	-0.045***	-0.202***	-0.065***
	(-14.19)	(30.25)	(-8.91)	(-17.27)	(-16.39)	(-3.65)	(15.44)	(-4.36)	(-9.12)	(-6.69)
BorrowerROA	-327.201***	0.573***	0.315***	-0.534**	-1.077***	-305.284***	0.222	0.762***	-0.372	-0.495***
	(-14.93)	(3.17)	(2.94)	(-2.22)	(-10.77)	(-7.51)	(0.57)	(4.38)	(-0.89)	(-3.41)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BorrowerBook Leverage	96.379***	0.569***	0.138***	0.085	0.393***	78.424***	0.407**	0.296***	-0.461***	0.306***
	(11.05)	(5.47)	(2.66)	(0.70)	(8.01)	(4.96)	(2.51)	(4.17)	(-2.68)	(4.69)
Borrowerity Tangibil	-8.425	-0.292***	-0.062	-0.044	-0.183***	21.894	-0.300	-0.104	0.042	-0.151*
	(-0.63)	(-2.61)	(-1.05)	(-0.29)	(-3.03)	(0.85)	(-1.55)	(-1.10)	(0.18)	(-1.74)
BorrowerCash Holding	-10.969	-0.746***	0.007	-0.111	-0.124	25.626	-0.362	0.316**	-0.661*	-0.280*
	(-0.63)	(-4.44)	(0.07)	(-0.47)	(-1.32)	(0.68)	(-1.03)	(2.30)	(-1.71)	(-1.79)
BankControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	301.170***	16.435***	4.242***	2.909***	1.394***	356.568***	17.048***	4.240***	2.883***	1.280***
	(15.81)	(71.09)	(32.11)	(10.24)	(12.65)	(8.06)	(42.18)	(23.80)	(6.42)	(7.65)
Adj.R^2	0.551	0.724	0.327	0.263	0.373	0.473	0.660	0.225	0.378	0.294
N	7191	7191	7157	7191	7191	2916	2916	2890	2916	2916

Table 2.6: Address Selection Bias Using Propensity Score Matching

This table presents the ordinary least square analysis results for the implications of multilevel closure to bank loan terms run on the sample matched using propensity score matching. Columns (1)-(5) show the results for credit lines, and Columns (6)-(10) show the results for term loans. The dependent variables are loan spread (Spread), the natural log of loan amount (Amount), the natural log of loan maturity (Maturity), the number of financial covenants (#Covenant), and collateral requirement (Collateral), respectively. The main independent variables are ClosureLead and CountClosureParti. Closure is a dummy variable equals to one if at least one bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise. It is the same as the count of closure lead bank. CountClosureParti is the number of participant banks in a loan syndicate that also lend to the supply chain partners of the borrower in the past three years. Variables in BankControls are BankSize, BankCapitalRatio, BankROA,TotalLoan, Liquidity, Efficiency, and MarketSensitivity. All regressions control for three-digit SIC industry fixed effects, lead bank fixed effects, and year fixed effects. t-statistics are reported in parentheses. The sample period is 2001-2020. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Credit Lines					**Term Loans**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Dependent Variables:	**Spread**	**Amount**	**Maturity**	**#Covenant**	**Collateral**	**Spread**	**Amount**	**Maturity**	**#Covenant**	**Collateral**
ClosureLead	7.633***	-0.047*	-0.029*	-0.054*	0.014	15.390***	0.004	0.022	-0.043	0.044***
	(3.18)	(-1.77)	(-1.96)	(-1.69)	(1.02)	(3.08)	(0.09)	(1.05)	(-1.15)	(2.65)
CountClosureParti	-2.978***	0.063***	0.020***	0.056***	-0.001	-9.151***	0.078***	0.001	0.086***	-0.016***
	(-6.16)	(9.84)	(5.31)	(8.13)	(-0.47)	(-8.67)	(6.72)	(0.28)	(8.00)	(-2.90)
RelIntensity	-17.678***	0.191***	-0.067***	0.136***	-0.055***	-30.516***	0.117**	-0.063**	0.291***	-0.038
	(-6.79)	(5.99)	(-4.67)	(3.82)	(-3.73)	(-4.78)	(1.99)	(-2.40)	(4.77)	(-1.52)
BorrowerSize	-17.949***	0.471***	-0.056***	-0.235***	-0.108***	-12.061***	0.444***	-0.045***	-0.193***	-0.069***
	(-15.90)	(31.36)	(-7.80)	(-15.56)	(-16.63)	(-4.60)	(15.61)	(-4.11)	(-8.10)	(-6.81)

BorrowerROA	-377.568***	0.952***	0.440***	-0.439	-1.260***	-402.578***	0.490	0.723***	-0.483	-0.672***
	(-17.37)	(4.41)	(3.39)	(-1.62)	(-10.87)	(-9.82)	(0.98)	(3.67)	(-1.01)	(-4.01)
BorrowerBook Leverage	95.546***	0.496***	0.105*	0.021	0.422***	85.388***	0.313*	0.279***	-0.616***	0.329***
	(10.51)	(4.39)	(1.94)	(0.16)	(8.02)	(5.16)	(1.76)	(3.70)	(-3.41)	(4.75)
Borrower Tangibility	-1.192	-0.357***	-0.057	-0.041	-0.161***	35.462	-0.255	-0.164	0.052	-0.125
	(-0.10)	(-2.86)	(-0.93)	(-0.24)	(-2.58)	(1.33)	(-1.10)	(-1.56)	(0.21)	(-1.33)
Borrower CashHolding	27.899	-1.053***	-0.039	-0.405	-0.069	52.663	-0.605	0.208	-0.737*	-0.311*
	(1.54)	(-5.63)	(-0.38)	(-1.57)	(-0.67)	(1.34)	(-1.57)	(1.41)	(-1.86)	(-1.86)
BankControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	302.936***	16.662***	4.388***	3.076***	1.414***	316.018***	17.086***	4.360***	3.025***	1.236***
	(15.49)	(64.71)	(31.55)	(10.34)	(12.20)	(7.04)	(39.55)	(22.69)	(6.56)	(7.21)
Adj.R^2	0.544	0.668	0.288	0.239	0.362	0.454	0.599	0.210	0.372	0.290
N	6565	6565	6565	6565	6565	2608	2608	2608	2608	2608

Table 2.7: Address Selection Bias Using Heckman Selection Model

This table presents the Ordinary least square analysis results for the implications of multilevel closure to bank loan terms. Columns (1)-(6) show the results for credit lines, and Columns (7)-(12) show the results for term loans. Columns (1) and (2) are the first stage regressions of Heckman selection model. The dependent variables in both the left and right panels are ClosureParti, loan spread (Spread), the natural log of loan amount (Amount), the natural log of loan maturity (Maturity), the number of financial covenants (#Covenant), and collateral requirement (Collateral), respectively. In Panel A, the main independent variables are ClosureLead and CountClosureParti. Closure is a dummy variable equals to one if at least one bank in a loan syndicate also lends to the supply chain partners of the borrower, zero otherwise. It is the same as the count of closure lead bank. CountClosureParti is the number of participant banks in a loan syndicate that also lend to the supply chain partners of the borrower in the past three years. In Panel B, the main independent variables are Closure and CountClosureParti. In addition, I control for BankCount, the number of banks in a syndicate and the interaction of CountClosureParti and BankCount to isolate the syndicate size effect from the effect of CountClosureParti. Variables in BankControls are BankSize, BankCapitalRatio, BankROA,TotalLoan, Liquidity, Efficiency, and MarketSensitivity. All regressions control for three-digit SIC industry fixed effects, lead bank fixed effects, and year fixed effects. I also include the coefficients of the inverse Mills ratio at the bottom. t-statistics are reported in parentheses. The sample period is 2001-2020. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Credit Lines						**Term Loans**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Dependent Variables:	**ClosureParti**	**Spread**	**Amount**	**Maturity**	**#Covenant**	**Collateral**	**ClosureParti**	**Spread**	**Amount**	**Maturity**	**#Covenant**	**Collateral**
ClosureLead	1.439***	-0.751	0.047*	0.009	-0.077**	-0.001	1.205***	14.880**	0.138**	0.045	-0.060	0.078***
	(42.25)	(-0.36)	(1.80)	(0.57)	(-2.38)	(-0.06)	(23.00)	(2.48)	(2.26)	(1.50)	(-0.93)	(2.93)

CountClosureParti		-2.441***	0.050***	0.017***	0.049***	0.000		-7.511***	0.065***	0.005	0.089***	-0.013***
		(-6.60)	(10.77)	(5.76)	(8.58)	(0.10)		(-7.81)	(6.68)	(0.97)	(8.59)	(-3.01)
RelIntensity	0.374***	-15.140***	0.156***	-0.093***	0.083**	-0.052***	0.443***	-19.643***	0.156**	-0.024	0.317***	-0.021
	(10.04)	(-6.28)	(5.18)	(-4.93)	(2.22)	(-3.39)	(8.15)	(-2.98)	(2.32)	(-0.74)	(4.50)	(-0.70)
BorrowerSize	0.164***	-19.250***	0.462***	-0.070***	-0.224***	-0.109***	0.106***	-19.016***	0.409***	-0.063***	-0.182***	-0.097***
	(16.37)	(-25.14)	(48.15)	(-11.58)	(-18.94)	(-22.35)	(7.03)	(-9.14)	(19.35)	(-6.17)	(-8.17)	(-10.49)
BorrowerROA	1.059***	-379.858***	0.934***	0.535***	-0.766***	-1.325***	1.240***	-406.371***	0.699*	1.019***	-0.407	-0.725***
	(4.67)	(-24.93)	(4.90)	(4.47)	(-3.25)	(-13.66)	(3.88)	(-10.02)	(1.70)	(5.10)	(-0.94)	(-4.03)
BorrowerBookLeverage	-0.339***	80.182***	0.423***	0.137***	0.023	0.427***	-0.548***	96.965***	0.283*	0.335***	-0.842***	0.419***
	(-3.22)	(12.48)	(5.25)	(2.73)	(0.23)	(10.45)	(-4.08)	(6.68)	(1.92)	(4.70)	(-5.43)	(6.51)

BorrowerTangibility	0.080	-6.357	-0.226**	0.010	-0.083	-0.164***	-0.074	32.970	-0.116	-0.070	-0.600**	-0.366***
	(1.06)	(-0.74)	(-2.11)	(0.15)	(-0.62)	(-3.00)	(-0.62)	(1.49)	(-0.51)	(-0.64)	(-2.51)	(-3.71)
BorrowerCashHolding	-0.635***	29.644**	-1.164***	0.064	-0.052	-0.029	-0.280	1.702	-0.589*	0.047	-0.521	-0.577***
	(-3.08)	(2.07)	(-6.50)	(0.57)	(-0.24)	(-0.32)	(-0.94)	(0.05)	(-1.77)	(0.29)	(-1.49)	(-3.98)
BankControls	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Inverse Mills Ratio		-16.6	0.1	0.0	-0.1	-0.1		-28.1	0.2	0.1	0.0	-0.1
N	7586	7586	7579	7586	7586	3071	3071	3071	3062	3071	3071	3071

CHAPTER 3. CORPORATE CAPITAL STRUCTURE AND FIRM VALUE: INTERNATIONAL EVIDENCE ON THE SPECIAL ROLES OF BANK DEBT[12]

Abstract

We contribute to the corporate capital structure and bank specialness literatures by studying the effects of bank debt on corporate value. We apply novel methodology to almost 60,000 firms in 110 countries over 17 years—over 300,000 total observations. We find that bank term loans and credit lines are strongly positively associated with firm value, but only when employed very intensively—at 90% or more of total corporate debt. These effects are consistent with bank specialness at high-intensity levels. These findings support previously untested theoretical predictions that bank specialness would be stronger or exist only at high bank debt intensities. Our results hold broadly but are stronger for credit-constrained firms—small firms and those in low-income countries. Channel analysis suggests that term loans boost short-term firm performance more, while credit lines better promote long-run growth. The findings suggest future research topics and have policy implications, particularly during the COVID-19 crisis.

3.1. Introduction

This paper builds on the corporate capital structure and bank specialness literatures to investigate whether and under what circumstances bank debt contributes positively to

[12] Coauthored with Allen N. Berger, Sadok El Ghoul, and Omrane Guedhami.

the value of a corporation. We employ an extensive dataset on debt structures of corporations around the world to address this question. Our findings strongly suggest that bank debt adds to corporate value, but only if the firm uses either bank term loans or credit lines very intensively—on the order of 90% or more of total corporate debt. Bank term loans have fixed amounts and maturities, while credit lines allow the borrower to draw down funds at its discretion any time until maturity. These are the two most frequently employed types of corporate debt, and more than one-third of our global sample of corporations use one or the other of two bank loan types at 90% or higher intensity. Thus, our findings suggest that bank debt can indeed increase corporate value, but only in circumstances characterized by high bank debt intensity.

Our paper contributes to the corporate capital structure literature, which investigates whether and how the proportions of a corporation's assets financed by different types of debt and equity matter to firm value. Part of this research focuses on the choices between equity and debt. This literature is largely based on deviations from Modigliani and Miller's (M&M, 1958) irrelevance proposition that in a world without frictions, the mix of debt and equity does not affect firm value. Building on this seminal work, the static trade-off model suggests that firms choose optimal capital structures by trading off the tax shield benefits of debt against financial distress, bankruptcy, and agency costs of debt (Leland, 1998). The pecking order model of Myers and Majluf (1984) shows how internal sources of funds may be preferred to both external debt and equity to finance investments and why debt may be chosen over equity under conditions in which management has information advantages over outsiders.[13] A third strand of the capital structure literature focuses on the choices between public debt (e.g., bonds) and private debt (e.g., bank loans). Existing theories provide several explanations for this decision, including the probability of inefficient liquidations, control of moral hazard problems, and cost of disclosure of proprietary information (e.g., Diamond, 1984, 1991; Chemmanur and Fulghieri, 1994; Hackbarth, Hennessy, and Leland, 2007; De Fiore and Uhlig, 2011).[14]

We also contribute to the bank specialness literature that focuses on the value creation of bank loans. Bank specialness generally refers to the value to the borrowing firm from bank loans that exceed the value provided by other types of firm debt. Theory suggests that this value derives from comparative advantages of banks over other debt providers in generating private information about the firms. These advantages occur in a) screening potential borrowers to make better loan contract terms and choices of which borrowers to approve before loans are issued; b) monitoring borrowers after loans are issued, observing the borrowers and intervening as necessary to promote prudent behavior; and c) using bank-firm relationships to extract private information while providing additional loans, deposits, and other financial services to the firms over the course of these relationships (e.g., Diamond, 1984; Fama, 1985; Berlin and Loeys, 1988).

Theory also suggests at least three reasons why bank specialness may be increasing in bank debt intensity, i.e., why bank loans might be more special or only special when

[13] Several studies provide empirical testing of these models, including Opler and Titman (1994), Graham (1996), Hovakimian, Opler, and Sheridan (2001), Frank and Goyal (2003), among others. For a survey of this literature, see Parsons and Titman (2009) and Graham and Leary (2011).

[14] Empirical studies on the choice between private and public debt include Houston and James (1996) and Johnson (1997), Denis and Mihov (2003), Dhaliwal, Khurana, and Pereira (2011), and Colla, Ippolito, and Li (2013), among others. See Colla, Ippolito, and Li (2020) for a survey of this literature.

they are used very intensively. First, there may be economies of scale in screening and monitoring, yielding more and/or better private information on borrowers when bank loans account for much more of the borrower's debt (e.g., Diamond, 1984, 1991; Ramakrishnan and Thakor, 1984; Boyd and Prescott, 1986). Second, relationship lending theory predicts more benefits when a bank holds a high percentage of the borrower's debt because the bank can reuse the private information in the expected future provision of lending and other services (e.g., Sharpe, 1990; Rajan, 1992; Petersen and Rajan, 1995; Boot and Thakor, 1994, 2000). Third, banks may invest more in screening, monitoring, and/or relationships when there are fewer non-bank debt holders that may be free-riding on the banks' efforts (e.g., Datta, Iskandar-Datta, and Patel, 1999). That is, banks may put in more effort when there are fewer non-bank debt holders that take advantage of the bank's work in bolstering the safety of and returns on the debt they provide.

Bank term loans and credit lines require somewhat different lending skills and technologies, and both are usually concentrated in a small number of banks or only one originating or lead bank. As noted above, over one-third of the firms in our global sample employ one or the other of these two bank loan types at 90% or higher intensity. These facts also suggest the possibility that bank specialness may require concentration in either term loans or credit lines. It is less likely that the marginal effect of other types of firm debt sold in public markets, such as bonds, would have much stronger effects at high intensities. Public debt is typically held much more diffusely, with limited benefits to any one debtholder from investing heavily in screening, monitoring, or relationships.

The empirical bank specialness literature includes event studies of the effects on firm value of bank loan announcements, as well as studies of the benefits to business borrowers of banking relationships, although these two strands of the specialness literature are usually considered to be free-standing. Both types of specialness studies fail to reach consensus on whether and the extent and circumstances under which bank lending is special, as shown in the brief literature reviews in Appendix A. As well, neither test for the theoretically predicted possibility that bank loans might be more special or only special when used very intensively. Thus, we provide the first empirical tests of this possibility. As will become clear, our regression results are consistent with all of the main predictions of the bank specialness theory – strong evidence of bank specialness, that this specialness applies only at high intensities of bank debt, and it applies separately for term loans and credit lines.

Our dataset covers over 300,000 firm-year observations from nearly 60,000 corporations in 110 countries from 2002 to 2018 using Capital IQ Capital Structure and Compustat datasets. We compare the effects on market-to-book ratios (MTB) of seven types of debt—bank term loans, bank credit lines, senior bonds and notes, subordinated bonds and notes, commercial paper, capital leases, and other debt—for a wide variety of corporations other than highly regulated financial firms and utilities.[15] We also collect a number of control variables for firms and countries, as well as several firm performance variables to use in our channel analysis.

Our empirical methodology uses regression splines to uncover the effects of the two types of bank debt that differ with their intensity of use. The results suggest that the effects of bank debt on corporate value are negative when term loans or credit lines are

[15] We are aware of only two other related studies that use the seven debt intensities, and investigate their determinants (John, Kaviani, Kryzanowski, and Maleki, 2018; Boubakri, Chen, El Ghoul, and Guedhami, 2020).

below about 90% of total corporate debt, and become sharply positive from 90% to 100%. The use of standard linear regressions only would incorrectly suggest that bank debt has only negative effects on borrower value and is not special.

We also address three potential identification concerns regarding why the observed effects may not reflect causality from the intense use of bank loans to corporate value. The first is reverse causality—more valuable firms may choose to borrow from banks more intensively. We deal with this concern by including a lagged value of the dependent variable MTB on the right-hand side to absorb much of these effects. We also lag the debt intensities by five years instead of one because a given year's performance is less likely to cause distant past debt choices. The second concern is selection bias—banks may specifically target and lend intensively to more valuable firms. To address this concern, we use a propensity score matching (PSM) approach, matching firms with intense bank lending with other comparable firms. The third identification issue is omitted variable bias—our results may be driven by causality from firm or country characteristics that are insufficiently controlled for in the regressions that cause both firm value and intensive bank lending. We confront this issue by flooding the models with various fixed effects and additional firm and country controls. In all of the checks addressing the three identification concerns, our main results continue to suggest that the marginal benefits on firm value of both term loans and credit lines above 90% of total debt exceed the marginal benefits of every other type of debt.

We also check whether our main results hold for various subsets of the data based on firm characteristics, country types, and time subperiods. Specifically, we investigate the effects for small, medium, and large firms, low- and high-leverage firms, low and high asset tangibility firms, and U.S listed versus non-U.S. listed firms. We also show findings for high- and low-income countries, bank-based and market-based economies, and the U.S and non-U.S. countries. To rule out that our findings are driven by the Global Financial Crisis (GFC), we additionally divide data by the years before 2007, 2007–2011, and 2012–2018. The results show that intensively held term loans and credit lines generate more marginal firm value than all other types of debt held in all cases except for term loans in the pre-2007 period. The subsample analysis demonstrates that our findings are highly robust and are not driven by any particular firm or country characteristic or any one time period. We also find significantly stronger effects for small firms and in low-income countries, consistent with banks providing the most value to customers facing the most financial constraints. Put another way, bank specialness works where it is most needed.

Finally, our channel analysis suggests that term loans and credit lines both work through many channels, but there are some important differences. Term loans tend to boost short-term firm performance more through return on assets (ROA) in the following year, while credit lines aid long-term firm performance more through asset growth, research and development (R&D) spending, and capital expenditures (CAPEX). These long-term benefits of credit lines are consistent with earlier findings that credit lines are more strongly associated with bank-borrower relationships and monitoring incentives for the banks over the course of these relationships. These relationships are well-known to last for many years and promote long-term positive outcomes for firms.

The remainder of this paper is organized as follows: Section 2 describes our data, sample, and summary statistics. Our main empirical results are in Section 3, identification challenges are addressed in Section 4, subsample analyses are presented in Section 5, and a channel analysis of the main results is in Section 6. Section 7 concludes and suggests some future research directions and policy implications. Appendix A provides a brief summary of bank specialness literature and Appendix B shows debt percentages and MTBs by country and by year.

3.2. Data and Variables

3.2.1. Sample

Our data are from two sources: The debt structure data are drawn from Capital IQ, and firms' income statement and balance sheet items are from Compustat's North America and Global files. We take the intersection of the two databases and retain the public firms from 2001 to 2018 because Capital IQ's coverage is limited prior to 2001. We drop highly regulated financial firms (SIC codes 6000–6999) and utilities (SIC codes 4900–4949). We also exclude firm-year observations with missing values of our main independent and dependent variables. We end up with 318,605 firm-year observations from 59,938 corporations in 110 countries.

3.2.2 Variables

We discuss our dependent, key independent, and control variables. All continuous variables are winsorized at the 1st and 99th percentiles.

3.2.2.1 Dependent Variables

Our main dependent variable is the market-to-book ratio (MTB), which is the market value of equity plus the book value of assets minus the book value of equity divided by the book value of assets (e.g., Claessens, Djankov, Fan, and Lang, 2002; Lins, 2003; Kalcheva and Lins, 2007).

3.2.2.2 Key Independent Variables

Capital IQ classifies corporate debt into seven mutually exclusive categories: term loans, credit lines, senior bonds and notes, subordinated bonds and notes, capital leases, commercial paper, and other debt. Capital IQ records the amount of credit lines that are drawn by firms. Term loans and credit lines are issued solely by commercial banks, which are our focus here. We compute the proportions of each type of debt, the amount of that type divided by the sum of the seven types of debt. We drop the "other debt" ratio from regressions to avoid perfect collinearity.

3.2.2.3 Controls

We use firm- and country-level control variables. At the firm level, we control for firm size, measured by the natural log of total assets in millions of U.S. dollars (Log(TA)); asset tangibility, measured by the ratio of property, plant, and equipment to total assets (PPE/TA); financial leverage, measured by the ratio of total debt to total assets (TD/TA); and a U.S. listing dummy that equals 1 if the firm is listed in the U.S. (US List) and 0 otherwise. At the country level, we control for GDP growth rate (GDP Growth) and the natural logarithm of GDP per capita (Log(GDP/Capita)).

3.2.3 Summary Statistics

Table 3.1 displays the summary statistics of the proportions of the seven debt types. The table shows that term loans are the most popular debt instrument—more than 75% of the firms in our sample have term loans on their balance sheets—and credit lines are the second most used. Thus, although all firms in our sample are publicly traded, bank debt is still the most important source of credit. The remaining debt types in order of decreasing intensity are senior bonds and notes, subordinated bonds and notes, capital leases, and commercial paper.

In Table 3.2, we divide the range of debt intensity variables into ten equal-length intervals. Since the variables are bounded by 0 and 1, the first interval is [0, 0.1), the second is [0.1, 0.2), and so on. The percentage in each cell indicates the relative frequency of the firms with proportions of that type of debt falling into the corresponding interval. For example, the first cell means that 29.0% of firms have 0% to 10% term loans in their total debts. Figure 3.1 plots the relative frequencies of each type of debt over the ten intervals. Figure 3.1 clearly illustrates that the distributions of bank term loans and credit lines are bimodal, with high frequencies in the top and bottom deciles, whereas the distributions of other types of debt variables are unimodal, with concentration only in the bottom decile. These characteristics are consistent with Colla, Ippolito, and Li's (2013) concept of debt specialization. Except for the debt type in which they choose to specialize, most firms use no more than 10% of other types of debt.

As indicated in the introduction, more than one-third of the sample shows very intense use of either bank term loans or credit lines. Term loans make up more than 90% of total debt for 29.4% of the observations, while the figure for credit lines is 7.0%.

Table 3.3, Panel A shows summary statistics of the dependent variables analyzed in the subsequent sections of the paper. They are market-to-book ratio (MTB), asset growth rate, return on assets, total dividends paid, research and development (R&D) expenditures, and capital expenditures. MTB is our main dependent variable and the others are employed in the channel analysis. Because we include many developing countries in our sample, we are not surprised to see that the first quartile of asset growth rate is negative, and that more than 25% of firms do not pay dividends. Finally, Table 3.3, Panel B contains the summary statistics for the control variables.

3.3. Methodology and Main Empirical Results

To test the valuation effects of the sources of bank debt, we estimate several specifications of the following regression model:

$$MTB_{i,j,k,t} = \beta_0 + \beta_1 Term\ Loans_{i,j,t} + \beta_2 Credit\ Lines_{i,j,t} + \beta_3 Senior\ Bonds_{i,j,t} + \beta_4 Subordinated\ Bonds_{i,j,t} + \beta_5 Capital\ Leases_{i,j,t} + \beta_6 Commercial\ Paper_{i,j,t} + \gamma CONTROLS_{i,j,k,t} + \mu_j + \mu_k + \mu_t + \varepsilon_{i,j,k,t}, \quad (1)$$

where *i*, *j*, *k*, and *t* index firms, industries, countries, and years, respectively. MTB is the dependent variable in all of our regressions except for the channel analysis. The variables *Term Loans* and *Credit Lines* are the intensities of the two types of bank debt, either the ratios of the two types of bank debt to total firm debt or the splines of these ratios. The variables *Senior Bonds*, *Subordinated Bonds*, *Capital Leases*, and *Commercial Paper* are the intensities of these other types of debt. *CONTROLS* is a vector of control variables, including firm size (log(TA)), tangibility (PPE/TA), leverage (TD/TA), U.S. listing dummy (US List), GDP Growth and GDP per capita (log(GDP/CAP)) of firms' home countries. The μ terms are industry, country, and year fixed effects. Standard errors are clustered at the firm level for all columns.

Table 3.4 reports the main results. Column (1) shows the linear model, where we use the proportions of term loans and credit lines as our main independent variables of interest, and the proportions of other corporate debt as controls. The results show that the intensities of credit lines and term loans are negatively associated with firm valuations at the 1% level. The coefficient of subordinated bonds intensity is negative at the 10% level, while the coefficients of the intensities of senior bonds, capital leases, and commercial paper are positive at the 1% level.

Were we to stop the analysis here and base our deductions solely on this limited evidence, we would reach the incomplete conclusion that banks are <u>not</u> special. This would follow because the measured marginal contributions of the two types of bank debt reduce firm value, while some other types of debt increase this value.

However, it does not make sense to stop the analysis here. As discussed in the introduction, the theory provides at least three reasons why bank specialness may be more in force or only in force when firms use bank debt very intensively. These are a) economies of scale in bank screening and monitoring; b) increasing relationship lending benefits at high intensity from reusing the private information in future services to the borrower; and c) increased bank effort in screening, monitoring and relationships when free-rider problems by other debt holders are reduced. It is therefore sensible to go beyond the linear model in Column (1) and consider functional forms in which the marginal effects of bank debt ratios may be positive at high bank debt intensities, despite the overall negative marginal effects.

While there are several ways to accomplish this, the statistics literature suggests that a spline regression model may be a superior choice. Such a model breaks the regression line into a number of line segments separated by breakpoints or spline knots. The regression line changes direction at these breakpoints, but does not jump at these points. The statistics literature suggests that splines may be more flexible than polynomial specifications such as quadratic or cubic regressions, and may be more efficient than kernel regressions (e.g., Marsh and Cormier, 2001). Spline models are also employed in the finance literature to address similar issues when linear models do not give complete answers (e.g., Morck, Shleifer, and Vishny, 1988; Boubakri, El Ghoul, Guedhami, and Megginson, 2018). However, as noted in the introduction, the empirical bank specialness research does not use spline models or consider other models to test the theoretical prediction that specialness differs by bank debt intensity.

We follow the prior statistics and finance literatures and show three spline models in Table 3.4 that allow the relations between the two types of bank debt and firm value to vary at different intensity levels. In Spline Model 1, we divide the intensities of term loans and credit lines into three spline variables with breakpoints of 20% and 80%.[16] We choose these specific breakpoints in the interest of symmetry and because the distributions of term loans and credit lines are bimodal, i.e., most observations are concentrated in the [0, 20) and [80, 100] intervals. We find that the coefficients of the first two spline variables of both term loans and credit lines are negative and significant at the 1% level. In contrast, however, the coefficients of the third spline variables for term loans and credit lines in the [80, 100] interval are significantly positive. These results are consistent with the theoretical

[16] Thus, in Spline Model 1, Term Loans [0, 20) equals Term Loans if Term Loans<20% and equals 20% otherwise. Term Loans [20, 80) equals 0 if Term Loans <20%, equals Term Loans minus 20% if 20%≤ Term Loans<80%, and equals 60% otherwise. Term Loans [80, 100] equals 0 if Term Loans≤ 80%, equals Term Loans minus 80% if 80%≤ Term Loans≤ 100%.

prediction that bank specialness may be primarily concentrated at high-intensity levels of bank debt.

Spline Model 2 adds a breakpoint at 90% because our univariate analysis shows that more than one-third of our sample had over 90% of their debt in bank term loans or credit lines, with much lower percentages in the [80, 90) interval. The results of Spline Model 2 show positive and significant coefficients for Term Loans [90, 100] and Credit Lines [90, 100] that are much larger than those in the [80, 100] interval in Spline Model 1. Spline Model 2 also reveals negative and significant coefficients for both term loans and credit lines in the [80, 90) interval. These findings provide strong evidence that the positive effects for [80, 100] shown in Spline Model 1 were driven by the observations in the [90, 100] range and suggest that the [80, 90) interval may be more appropriately grouped with the negative effects of lower ranges.

We therefore move to our final and what we believe is our best specification in Spline Model 3 that uses 20% and 90% as two breakpoints. We find negative effects that are decreasing in magnitude for the first two spline variables and positive effects when term loan or credit line intensities are over 90%. For each percentage point increase in term loan and credit line intensity above 90%, firm value rises by about 1.6% and 1.2%, respectively. These effects are highly economically significant and are at least twice the size of the effects for the other types of debt. They provide clear evidence of bank specialness, but only at high intensity levels.[17] Figure 3.2 plots average MTB against term

[17] We confirm these conclusions by rerunning the linear model on a subsample with only firms using more than 90% of either type of bank debt. The coefficients of term loans and credit lines turn significantly positive, indicating robustness.

loans and credit lines over the three intervals in Spline Model 3. In all of our subsequent regressions, we employ focus on Spline Model 3.

These results may help explain some of the mixed empirical findings in the empirical bank specialness research that does not account for the possiblity that this specialness may differ by bank debt intensity. The earlier findings supporting bank specialness may have been dominated by observations of high bank debt intensity, while those finding against specialness may have had more observations with modest bank debt usage. Further investigation of this issue is beyond the scope of this paper.

3.4. Identification Concerns

As discussed in the introduction, we have three main identification concerns—reasons why our main results may not reflect causality from intense use of bank loans to corporate value. These are reverse causality bias, selection bias, and omitted variable bias. We address these in Table 3.5.

To deal with reverse causality, we would ideally implement instruments that affect bank term loan and credit line intensities, but with no direct effects on MTB. However, finding shocks like these in 110 countries is not possible. Instead, we try two different methods. We include lagged MTB as an additional control in Panel A, Column (1). If more valuable firms choose to borrow intensively from banks, they likely did so last year as well, so lagged MTB may soak up this effect (e.g., Klein, 1998; Harford, Mansi, and Maxwell, 2008; Chen, Chen, and Wei, 2011). We also lag bank debt intensities and other debt intensities by five years in Panel A, Column (2). This may mitigate the problem, given that this year's performance is less likely to cause distant past debt choices.

In both columns, the relations between bank debt and firm value persist, and the coefficients for Term Loans[90, 100] and Credit Lines[90, 100] are positive. Most importantly, the coefficients for Term Loans[90, 100] and Credit Lines[90, 100] have the largest magnitude among the spline variables and other debt intensities, suggesting that the specialness of bank debt holds in these columns.

To alleviate selection bias concerns, we try to ensure that firms with intense bank lending are as similar as possible to other firms in the regression sample that do not have intense bank lending. We use propensity score matching (PSM) to address this problem. We identify all firms with 90% or higher term loans or credit lines and match them by PSM with non-intense bank borrowers. We conduct a one-to-one match without replacement and a one-to-three match between the treated and the control groups, respectively, on firm characteristics, including total assets, tangibility, leverage, and listing status on major U.S. exchanges. Thereafter, we run our spline regression on each of the matched samples. In Table 3.5, Panel A, Columns (3) and (4) display the regression results. The relations between intensities of term loans and credit lines can be found in both columns. The coefficients for Term Loans[90, 100] and Credit Lines[90, 100] are economically and statistically significant and exceed the effects of all other debt sources, suggesting that selection bias does not appear to explain our main findings.

Finally, we address omitted variable bias, in which other variables may cause both our main independent and dependent variables. It is plausible that unobserved firm characteristics, time-varying industry trend and country trends can drive the increases in both the use of bank debt and firm value. To tackle the omitted variable bias, we use a variety of fixed effects and add additional firm and country control variables. In Panel B of Table 3.5, we use firm and year fixed effects in Column (1), industry, country-cross-year fixed effects in Column (2), firm, country-cross-year fixed effects in Column (3), and industry-cross-country-cross year fixed effects in Column (4). In Panel C of Table 3.5, we include a variety of firm- and country-level control variables. The relations between bank debt and firm value exist in all columns, and the coefficients for Term Loans[90, 100] and Credit Lines[90, 100] are both economically and statistically significant and exceed the effects of all other debt sources, consistent with our main results.

3.5. Subsample Analysis

We perform a number of subsample analyses in Table 3.6. We divide our sample separately by firm characteristics, the characteristics of firms' countries of incorporation, and time subperiods. Panel A compares subsamples of small, medium, and large firms, low- and high-leverage firms, low and high asset tangibility firms, and U.S listed versus non-U.S. listed firms. To be clear, U.S. listed versus non-U.S. listed status differs from country of incorporation—many foreign firms list on exchanges in the U.S. to gain better access to capital. Panel B shows results for high- and low-income countries, bank-based and market-based nations, and incorporation in the U.S. versus the rest of the world.[18] Panel C shows subperiods of the years before 2007, 2007–2011, and 2012–2018, where the middle period represents the greatest effects of the GFC.

We have two goals for the subsample analysis. First, we want to determine whether the results are largely driven by any particular firm, country, or time period characteristics versus the results are generally robust across these characteristics. Second, we test whether

[18] The bank-based versus market-based financial system classification follows Demirguc-Kunt and Levine (1999).

some of the relative magnitudes of the measured effects line up with predictions from the literature.

Beginning with the results for small, medium, and large firms in Panel A, Columns (1)–(3), the banking literature suggests that small firms might get the most benefit from bank specialness. These firms tend to be the most bank-dependent and financially constrained (e.g., Berger, Bouwman, and Kim, 2017; Berger, Chen, El Ghoul, and Guedhami, 2020). While the effects are strongest for small firms, the empirical results nonetheless suggest that small firms do not drive the overall bank specialness findings. The results indicate that bank specialness at high intensity holds robustly for both term loans and credit lines for all three size classes.

Turning to the comparison of firms by low and high leverage in Columns (4)–(5), we recognize the possibility that the choice of bank debt may be used to optimize leverage, as in Johnson (1998). We find similar results showing bank specialness for both leverage categories, again suggesting robustness and that leverage decisions do not affect our main results. Columns (6)–(8) analyze the role of informational transparency using asset tangibility and U.S. listing status to see if the effects of bank debt are related to this transparency (e.g., Dass and Massa, 2011). Again, the results are robust across categories and are not driven by this firm characteristic.

Turning to the results by country characteristics in Panel B, we investigate the possibility that firms in low-income countries could explain our main findings, given that they are more often financially constrained, analogous to the argument for small firms above. Similarly, the results could be concentrated in countries with bank-based financial systems or those incorporated outside the U.S. that tend to have lower incomes. The coefficients in Panel B show robustness throughout, suggesting that none of these country characteristics drives our main results. The other notable finding is that the results are clearly stronger for firms in low- rather than high-income countries.

The subperiods analysis in Panel C indicate that no single time explains our results, although they are strongest after the GFC. This panel also shows our single case of non-robustness—term loans do not show the effects of bank debt specialness at high intensity during the short period prior to 2007—although credit lines do so during this period. Thus, we have some evidence of this specialness in every period.

We also conduct formal econometric tests of the two key comparisons by firm size and national income that were expected *ex ante*—that the results are stronger for small firms and those in low-income nations that are generally more financially constrained. Our Wald tests of the null hypothesis that the effects of term loans and credit lines in the [90, 100] interval are equal for small, medium, and large firms reject this null at the 10% level for term loans and the 5% level for credit lines. The null of equality for low- and high-income nations is rejected at the 1% for both credit types. Thus, while our main findings are strongly robust across firm and country characteristics and time periods, we can also conclude that bank debt at high intensity is significantly stronger for small firms and those in low-income nations.

3.6. Channel Analysis

Table 3.7 presents the various channels through which bank loan intensity may influence firm valuation. These channels are: asset growth rate, profitability, total dividends paid, cash holdings, R&D expenditures, and capital expenditures. We find that term loans and credit lines do not always work through the same channels, although both work through the dividend-paying channel and the cash-holding channel. Moreover, we find that term loans also work through the profitability channel since we observe that an increase in term loan intensity at time t-1 has a positive and significant effect on return on assets in the next period. We also find that credit lines work through the asset growth channel, R&D expenditure channel, and capital expenditure channel, which are long-term oriented.

The long-term benefits of credit lines are consistent with earlier findings that credit lines are more strongly associated with bank-borrower relationships (Berger and Udell, 1995) and provide banks with on-going monitoring incentives over the course of these relationships (Berger, Zhang, and Zhao, 2020). Bank-borrower relationships are by their very nature more long-term oriented than transactions loans that are based on information gathered at the time of loan applications. Other research also finds that firms with strong banking relationships tend to pay more dividends and spend more on capital expenditures and innovation (e.g., Herrera and Minetti, 2007; Acharya, Almeida, Ippolito, and Perez, 2014). Thus, credit lines appear to work more through long-term growth channels because they build relationships that enhance long-term firm performance, which is less often the case for term loans.

3.7. Conclusions, Future Research Suggestions, and Policy Implications

We contribute to the corporate capital structure and bank specialness literatures with a novel methodology, a large international dataset, and many identification, subsample, and channel analyses. Our findings strongly and robustly suggest that bank term loans and credit lines are special, but only when employed very intensively, which occurs for slightly over one-third of corporations. The data also suggest that the findings are strongest where bank credit is most important—for small firms and those in low-income countries that are most often financially constrained. Some of the findings imply that credit lines are more effective for promoting long-term firm performance, while term loans help boost firm performance relatively more in the short term.

We suggest additional future research using these methods and data to confirm and extend our results. As discussed, the theoretical predictions of bank specialness primarily or only at high bank debt intensities has never previously been tested, so more empirical confirmation of this theory appears to be in order.

However, it may be even more productive to conduct future theoretical and empirical research on our "bank unspecialness" findings. We have strong findings suggesting that bank loans reduce corporate value for almost two-thirds of corporations. We are unaware of any theoretical research motivating such findings or empirical research corroborating them, and we encourage both theorists and empiricists to investigate this issue further.

Our findings may also have policy implications, particularly during times of crisis, such as the COVID-19 crisis underway at the time of writing. As examples, U.S. policymakers have in some cases sought to help the corporate sector during this crisis through non-bank financial markets, such as bond market purchases by the Federal Reserve. In other cases, they have sought to shore up credit to firms through banks, such as the Paycheck Protection Program (PPP), and stress test restrictions on capital payouts by banks.

Our findings suggest that such policies by policymakers in the U.S. and around the world may help different groups of firms. Smaller firms and those in low-income nations that borrow very intensively from banks may be better served by policies that boost bank credit. For these firms, bank debt is special and promotes firm value. In contrast, medium and large firms and those in high-income nations that borrow less intensively from banks may be better off with policies focused on bond and other non-bank financial markets. For these firms, bank loans appear to be “unspecial” and harm firm value.

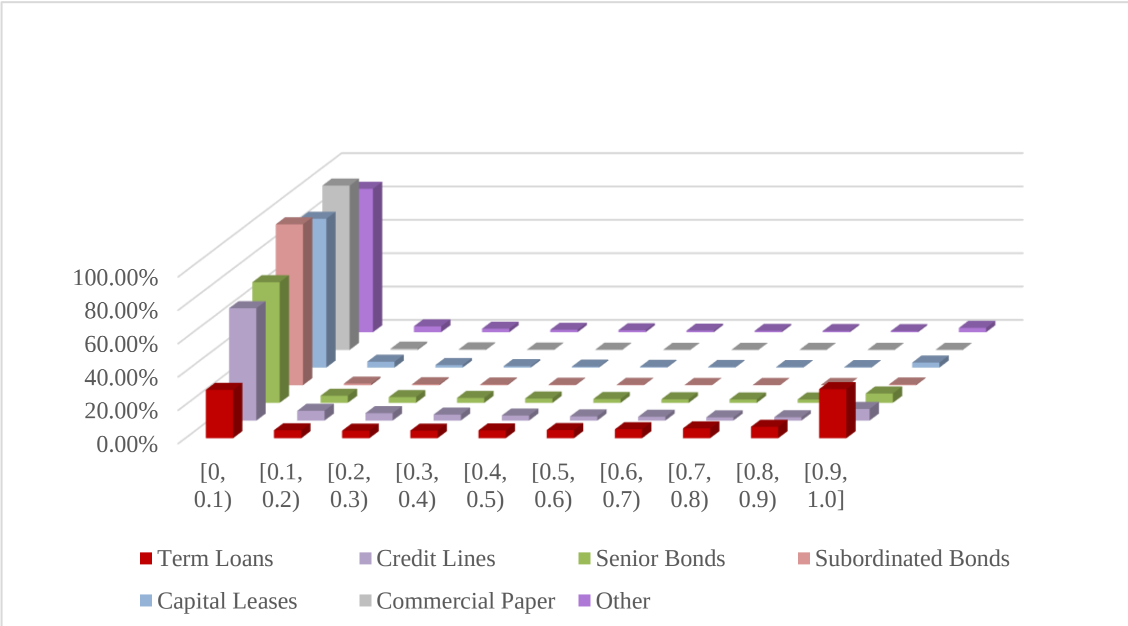


Figure 3.1 Relative Frequencies of the Seven Types of Debt.

This figure shows the relative frequencies of the seven types of debt variables over their deciles.

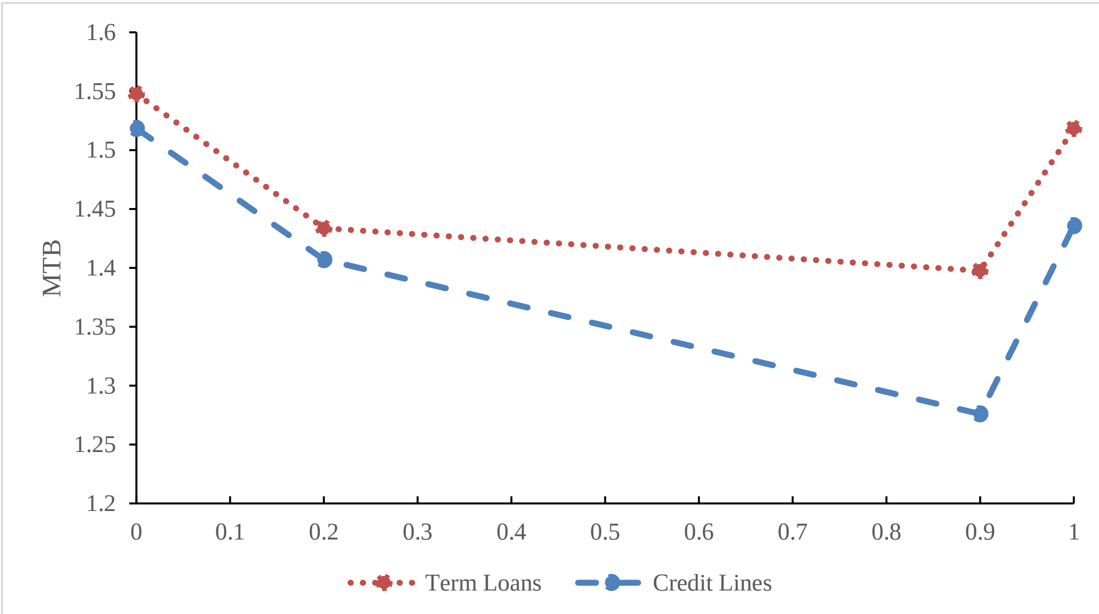


Figure 3.2 Bank Loan Intensities and MTB.

This figure plots the expected values for market-to-book ratio (MTB) against term loans and credit lines over the intervals [0, 20%), [20%, 90%), and [90%, 100%].

Table 3.1: Summary Statistics on Debt Structure

This table presents summary statistics on the ratios of different debt types to total debt, where total debt equals the sum of the seven types of debt. The sample size is 318,605.

	Mean	**SD**	**P25**	**Median**	**P75**
Term Loans	0.510	0.402	0.031	0.544	0.947
Credit Lines	0.181	0.306	0.000	0.000	0.240
Senior Bonds	0.159	0.295	0.000	0.000	0.174
Subordinated Bonds	0.016	0.095	0.000	0.000	0.000
Capital Leases	0.059	0.191	0.000	0.000	0.011
Commercial Paper	0.005	0.040	0.000	0.000	0.000
Other Debt	0.071	0.204	0.000	0.000	0.002

Table 3.2: Relative Frequencies of Debt Types

This table presents the relative frequencies of the seven types of debt over their deciles.

	[0, 0.1)	**[0.1, 0.2)**	**[0.2, 0.3)**	**[0.3, 0.4)**	**[0.4, 0.5)**	**[0.5, 0.6)**	**[0.6, 0.7)**	**[0.7, 0.8)**	**[0.8, 0.9)**	**[0.9, 1.0]**
Term Loans	0.290	0.048	0.045	0.046	0.047	0.049	0.054	0.059	0.069	0.294
Credit Lines	0.674	0.059	0.045	0.036	0.030	0.025	0.023	0.020	0.020	0.070
Senior Bonds	0.724	0.043	0.035	0.030	0.027	0.023	0.022	0.020	0.021	0.057
Subordinated Bonds	0.965	0.010	0.006	0.004	0.003	0.003	0.002	0.002	0.001	0.004
Capital Leases	0.892	0.035	0.015	0.009	0.006	0.004	0.003	0.003	0.003	0.030
Commercial Paper	0.985	0.007	0.003	0.002	0.001	0.001	0.000	0.000	0.000	0.000
Other Debt	0.860	0.036	0.021	0.015	0.012	0.010	0.008	0.007	0.007	0.026

Table 3.3: Summary Statistics for Dependent and Control Variables

This table presents the summary statistics for dependent and control variables. Panel A contains the summary statistics for dependent variables. MTB is the ratio of the market value of assets to the book value of assets, where the market value of assets is the market value of equity minus the book value of equity plus the book value of assets. AGROW is the growth rate of total assets from year *t*-1 to year *t*. ROA is return on assets. DIV/TA is the ratio of total dividends paid over total assets. CASH/TA is the ratio of cash and cash equivalents over total assets. R&D/TA is research and development expenditures over total assets. CAPEX/TA is the ratio of capital expenditures over total assets. Panel B presents the summary statistics for the control variables. TA is total assets in U.S. dollars. PPE/TA is the ratio of property, plant, and equipment over total assets. TD/TA is the ratio of total debt over total assets. US List is a dummy variable that equals 1 if a firm is listed on major U.S. exchanges, and 0 otherwise. GDP/CAP is GDP per capita in U.S. dollars. GDP Growth is the growth rate of a country's GDP from year t-1 to year t. In all our regressions, we use the logarithm of TA and GDP/CAP.

	N	**Mean**	**SD**	**P25**	**Median**	**P75**
Panel A. Dependent Variables						
MTB	318,605	1.531	1.269	0.921	1.124	1.632
AGROW	318,605	0.070	0.288	-0.055	0.049	0.168
ROA	316,951	0.052	0.165	0.024	0.072	0.123
DIV/TA	203,981	0.015	0.024	0.000	0.006	0.018
CASH/TA	295,774	0.135	0.144	0.034	0.088	0.183
R&D/TA	108,505	0.047	0.100	0.003	0.014	0.041
CAPEX/TA	287,524	0.048	0.059	0.011	0.029	0.062
Panel B. Control Variables						

TA	318,605	6,021.510	79,483.490	58.790	238.160	1,017.160
PPE/TA	318,605	0.232	0.180	0.066	0.209	0.363
TD/TA	318,605	0.245	0.189	0.089	0.213	0.361
US List	318,605	0.232	0.423	0.000	0.000	0.000
GDP/CAP	1,691	9.210	1.460	8.160	9.400	10.460
GDP Growth	1,691	0.079	0.082	0.016	0.034	0.054

Table 3.4: Main Results

This table presents the regression results for our main analysis. The dependent variable is MTB, the ratio of the market value of assets to the book value of assets, where the market value of assets is the market value of equity minus the book value of equity plus the book value of assets. In the Linear Model, we use the proportions of term loans and credit lines as our main independent variables. In Spline Model 1, we spline the proportions of term loans and credit lines into three intervals. Term Loans [0, 20) equals Term Loans if Term Loans<20% and equals 20% otherwise. Term Loans [20, 80) equals 0 if Term Loans <20%, equals Term Loans minus 20% if 20%≤ Term Loans<80%, and equals 60% otherwise. Term Loans [80, 100] equals 0 if Term Loans≤ 80%, and equals Term Loans minus 80% if 80%≤ Term Loans≤ 100%. The spline variables for the credit lines are defined similarly. In Spline Model 2, we spline the proportions of term loans and credit lines into four intervals—[0, 20), [20, 80), [80, 90), and [90, 100]. Spline Model 3, which is our final specification that we carry through the remainder of the paper, employs the three intervals of [0, 20), [20, 90), and [90, 100]. The control variables are the proportions of senior bonds and notes, subordinated bonds and notes, capital leases, commercial paper, the logarithm of total assets in U.S. dollars (Log (TA)), the ratio of property, plant, and equipment over total assets (PPE/TA), an indicator if a firm is listed in the U.S. (US List), the growth rate of GDP (GDP Growth), and logarithm of GDP per capita in U.S. dollars (Log (GDP/CAP)). We drop other debt to avoid perfect collinearity. We use industry (classified using 4-digit SIC code), year, and country fixed effects in all three models. Robust standard errors are clustered at the firm level. *t*-statistics are presented in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Linear Model	**Spline Model 1**	**Spline Model 2**	**Spline Model 3**
Term Loans	-0.201***			
	[-8.74]			
Credit Lines	-0.0662***			
	[-3.13]			

Term Loans [0, 20)	-0.569***	-0.656***
	[-10.11]	[-9.77]
Term Loans [20, 80)	-0.185***	0.0116
	[-5.61]	[0.42]
Term Loans [80, 90)		-0.576***
		[-4.75]
Term Loans [80, 100]	0.587***	
	[5.54]	
Credit Lines [0, 20)	-0.577***	-0.630***
	[-8.62]	[-11.16]
Credit Lines [20, 80)	-0.0573**	-0.113***
	[-2.10]	[-3.39]

Credit Lines [80, 90)		-1.030***	
		[-4.51]	
Credit Lines [80, 100]	0.529***		
	[8.97]		
Term Loans [0, 20)			-0.557***
			[-10.16]
Term Loans [20, 90)			-0.187***
			[-6.25]
Term Loans [90, 100]		1.522***	1.598***
		[11.12]	[7.47]
Credit Lines [0, 20)			-0.571***
			[-8.84]
Credit Lines [20, 90)			-0.0514**
			[-2.07]
Credit Lines [90, 100]		2.165***	1.207***
		[7.75]	[10.84]

Senior Bonds	0.242***	0.256***	0.256***	0.255***
	[9.86]	[10.44]	[10.46]	[10.43]
Subordinated Bonds	-0.0767**	-0.0703*	-0.0707*	-0.0713*
	[-2.01]	[-1.86]	[-1.87]	[-1.88]
Capital Leases	0.112***	0.134***	0.136***	0.138***
	[3.55]	[4.23]	[4.31]	[4.36]
Commercial Paper	0.607***	0.632***	0.628***	0.627***
	[6.51]	[6.78]	[6.75]	[6.73]
Log (TA)	-0.134***	-0.130***	-0.130***	-0.130***
	[-36.24]	[-35.28]	[-35.18]	[-35.22]
PPE/TA	-0.380***	-0.367***	-0.365***	-0.366***
	[-14.88]	[-14.43]	[-14.39]	[-14.40]
TD/TA	0.0307	0.111***	0.121***	0.119***
	[1.22]	[4.38]	[4.80]	[4.72]

US List	0.394***	0.395***	0.394***	0.394***
	[17.27]	[17.38]	[17.37]	[17.37]
GDP Growth	1.942***	1.964***	1.977***	1.972***
	[15.16]	[15.34]	[15.43]	[15.39]
Log (GDP/CAP)	0.129***	0.122***	0.120***	0.121***
	[7.38]	[6.94]	[6.80]	[6.87]
Constant	0.975***	1.047***	1.066***	1.053***
	[5.62]	[6.03]	[6.13]	[6.06]
Country, Industry, & Year Fixed Effects	Yes	Yes	Yes	Yes
N	318,543	318,543	318,543	318,543
Adj. R^2	0.213	0.216	0.216	0.216

Table 3.5: Identification Concerns

This table presents the results from the analyses that address identification concerns. We use Spline Model 3 from Table 3.4 where we spline Term Loans and Credit lines using the three intervals—[0, 20), [20, 90), and [90, 100]. Dependent variable is market-to-book ratio (MTB). In Panel A, Column (1) uses MTB lagged for one period as additional controls. Column (2) uses spline variables and intensities for non-bank debt that are lagged for 5 years. Columns (3) and (4) display the results using propensity score matched samples with n=1 without replacement and n=3, respectively. In Panel B, Column (1), we use firm and year fixed effects, in Column (2), we use industry (classified using 4-digit SIC code), country-cross-year fixed effects, in Column (3), we use firm, country-cross-year fixed effects, and in Column (4), we use country-cross-industry-cross-year fixed effects. In Panel C, Columns (1)–(3) contain firm age, analyst coverage (log(1+number of analysts covering a firm)), and stock illiquidity, respectively. Columns (4)–(7) add investor protection, creditor rights, information sharing, and disclosure standard into the regressions, respectively. Robust standard errors are clustered at the firm level. *t*-statistics are presented in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Reverse Causality and Sample Selection

	(1)	**(2)**	**(3)**	**(4)**
	lagged MTB	**Lag 5**	**PSM, exact match**	**PSM, neighbor=3**
Term Loans [0, 20)	-0.136***	-0.464***	-0.453***	-0.519***
	[-4.60]	[-5.68]	[-5.12]	[-7.05]
Term Loans [20, 90)	-0.001	0.0179	-0.088***	-0.0677**
	[-0.07]	[0.59]	[-2.68]	[-2.48]

Term Loans [90, 100]	0.200***	0.583***	1.224***	1.239***
	[3.75]	[4.23]	[9.54]	[10.70]
Credit Lines [0, 20)	-0.092***	-0.244***	-0.542***	-0.532***
	[-3.64]	[-3.41]	[-7.39]	[-8.73]
Credit Lines [20, 90)	-0.059***	-0.124***	-0.246***	-0.212***
	[-4.19]	[-3.20]	[-6.44]	[-6.52]
Credit Lines [90, 100]	0.480***	1.023***	1.906***	1.705***
	[4.71]	[3.32]	[7.68]	[7.58]
Senior Bonds	0.086***	0.155***	0.223***	0.252***
	[7.81]	[5.27]	[6.92]	[9.29]
Subordinated Bonds	0.004	0.092	-0.006	-0.062
	[0.23]	[1.54]	[-0.10]	[-1.45]

Capital Leases	0.0202	0.113***	0.117***	0.134***
	[1.42]	[2.72]	[2.96]	[4.04]
Commercial Paper	0.158***	0.433***	0.460***	0.539***
	[4.97]	[4.93]	[3.56]	[4.53]
Log (TA)	-0.036***	-0.065***	-0.132***	-0.129***
	[-25.55]	[-13.02]	[-30.57]	[-33.13]
PPE/TA	-0.050***	-0.305***	-0.361***	-0.375***
	[-4.57]	[-8.78]	[-12.32]	[-14.02]
TD/TA	0.0697***	-0.0584*	0.055*	0.0834***
	[6.04]	[-1.66]	[1.81]	[3.05]

US List	0.110***	0.319***	0.437***	0.406***
	[13.33]	[11.17]	[12.30]	[14.04]
GDP Growth	0.537***	1.273***	1.932***	2.013***
	[6.69]	[7.61]	[11.60]	[14.15]
Log (GDP/CAP)	-0.138***	0.0373	0.187***	0.144***
	[-16.81]	[1.38]	[8.62]	[7.57]
Lag MTB	0.699***			
	[177.86]			
Constant	1.960***	1.462***	0.445**	0.836***
	[24.01]	[5.38]	[2.07]	[4.45]
Country, Industry, & Year Fixed Effects	Yes	Yes	Yes	Yes
N	318,543	146,057	191,480	260,972
Adj. R^2	0.611	0.189	0.213	0.212

Panel B. Different Fixed Effect Models to Address Omitted Variable Bias

	(1)	(2)	(3)	(4)
Term Loans [0, 20)	-0.070	-0.589***	-0.0549	-0.577***
	[-1.51]	[-9.09]	[-1.20]	[-6.93]
Term Loans [20, 90)	-0.030*	-0.0552**	-0.0241	-0.0542*
	[-1.67]	[-2.21]	[-1.36]	[-1.75]
Term Loans [90, 100]	0.323***	1.231***	0.301***	1.044***
	[3.90]	[11.07]	[3.70]	[7.74]
Credit Lines [0, 20)	-0.123***	-0.573***	-0.143***	-0.487***
	[-3.08]	[-10.38]	[-3.66]	[-7.00]

Credit Lines [20, 90)	-0.038*	-0.180***	-0.0272	-0.245***
	[-1.75]	[-6.00]	[-1.28]	[-6.40]
Credit Lines [90, 100]	0.415***	1.528***	0.421***	1.476***
	[2.65]	[7.17]	[2.75]	[5.71]
Senior Bonds	0.000	0.250***	0.000	0.231***
	[0.02]	[10.12]	[-0.01]	[7.38]
Subordinated Bonds	-0.098**	-0.062	-0.112**	-0.239***
	[-2.15]	[-1.60]	[-2.45]	[-4.84]
Capital Leases	0.067***	0.131***	0.0700***	0.110***
	[2.72]	[4.12]	[2.85]	[2.75]
Commercial Paper	0.000	0.654***	0.0115	0.770***

	[0.01]	[6.97]	[0.22]	[7.43]
Log (TA)	-0.360***	-0.133***	-0.353***	-0.147***
	[-44.21]	[-35.47]	[-42.42]	[-31.08]
PPE/TA	-0.203***	-0.364***	-0.229***	-0.349***
	[-6.47]	[-14.31]	[-7.35]	[-10.11]
TD/TA	0.125***	0.131***	0.160***	0.196***
	[4.48]	[5.18]	[5.76]	[6.08]
US List		0.398***		0.388***
		[17.53]		[14.50]
GDP Growth	1.568***			
	[14.25]			
Log (GDP/CAP)	0.325***			
	[17.82]			
Constant	0.339**	2.318***	3.529***	2.402***
	[2.04]	[77.05]	[73.55]	[64.03]

Fixed Effects	Firm & Year	Country×Year, Industry	Country×Year, Firm	Country×Industry× Year
N	313,486	318,459	313,400	265,935
Adj. R^2	0.648	0.237	0.669	0.269

Panel C. Additional Firm- and Country-Level Control Variables to Address Omitted Variable Bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Term Loans [0, 20)	-0.575***	-0.729***	-0.617***	-0.621***	-0.579***	-0.584***	-0.582***
	[-8.92]	[-9.41]	[-9.77]	[-8.98]	[-8.46]	[-8.47]	[-8.43]
Term Loans [20, 90)	-0.049**	-0.0475	-0.070***	-0.056**	-0.037	-0.038	-0.0401
	[-1.98]	[-1.51]	[-2.92]	[-2.12]	[-1.37]	[-1.40]	[-1.48]
Term Loans [90, 100]	1.157***	1.361***	1.234***	1.062***	1.423***	1.439***	1.422***
	[10.40]	[9.16]	[11.25]	[8.82]	[11.91]	[11.98]	[11.80]
Credit Lines [0, 20)	-0.551***	-0.299***	-0.390***	-0.704***	-0.506***	-0.511***	-0.518***
	[-10.06]	[-4.42]	[-7.40]	[-11.88]	[-8.69]	[-8.74]	[-8.81]
Credit Lines [20, 90)	-0.189***	-0.139***	-0.196***	-0.174***	-0.187***	-0.189***	-0.187***
	[-6.31]	[-3.46]	[-6.69]	[-5.39]	[-5.85]	[-5.85]	[-5.79]
Credit Lines [90, 100]	1.579***	0.932***	1.460***	1.602***	1.687***	1.720***	1.684***
	[7.39]	[3.05]	[6.60]	[6.95]	[7.45]	[7.54]	[7.37]

Senior Bonds	0.259***	0.0651**	0.117***	0.258***	0.274***	0.273***	0.274***
	[10.56]	[2.19]	[5.00]	[9.81]	[10.31]	[10.21]	[10.18]
Subordinated Bonds	-0.071*	-0.116***	-0.055	-0.076*	-0.039	-0.042	-0.043
	[-1.89]	[-2.62]	[-1.42]	[-1.82]	[-0.93]	[-1.01]	[-1.03]
Capital Leases	0.134***	0.108**	0.132***	0.110***	0.135***	0.134***	0.134***
	[4.25]	[2.49]	[4.15]	[3.30]	[4.03]	[3.97]	[3.96]
Commercial Paper	0.648***	0.275***	0.417***	0.611***	0.589***	0.592***	0.590***
	[6.95]	[3.20]	[5.62]	[5.59]	[5.95]	[5.94]	[5.88]
Log (TA)	-0.121***	-0.207***	-0.081***	-0.133***	-0.126***	-0.126***	-0.127***
	[-31.04]	[-36.55]	[-23.01]	[-33.32]	[-32.70]	[-32.66]	[-32.90]
PPE/TA	-0.362***	-0.210***	-0.304***	-0.423***	-0.377***	-0.380***	-0.379***
	[-14.24]	[-6.21]	[-12.13]	[-15.04]	[-13.86]	[-13.92]	[-13.84]
TD/TA	0.109***	-0.172***	-0.040	0.197***	0.095***	0.093***	0.102***
	[4.29]	[-4.90]	[-1.60]	[7.21]	[3.53]	[3.45]	[3.77]
US List	0.401***	0.293***	0.345***	0.394***	0.375***	0.376***	0.379***
	[17.66]	[11.69]	[13.79]	[16.49]	[15.79]	[15.77]	[15.82]

GDP Growth	1.972***	2.915***	1.217***	2.254***	2.252***	2.314***	2.243***
	[15.41]	[15.01]	[9.82]	[16.63]	[16.21]	[16.81]	[16.28]
Log (GDP/CAP)	0.109***	0.193***	0.258***	-0.078***	0.098***	0.073***	0.103***
	[6.16]	[7.63]	[13.63]	[-3.58]	[5.23]	[3.80]	[5.40]
Firm age	-0.009***						
	[-10.29]						
Analyst Coverage		0.353***					
		[35.35]					
Stock Illiquidity			-21.76***				
			[-13.07]				
Investor Protection				0.000**			
				[2.02]			
Creditor Rights					-0.050***		
					[-4.89]		
Information Sharing						-0.038***	

						[-6.40]	
Disclosure							-0.019***
							[-2.91]
Constant	0.633**	-0.395**	-0.510***	3.029***	1.261***	1.504***	1.218***
	[2.46]	[-2.12]	[-2.75]	[13.86]	[6.85]	[7.92]	[6.47]
Country, Industry, & Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	128,355	261,716	261,716	242,942	285,450	283,935	281,431
Adj. R^2	0.294	0.215	0.214	0.228	0.219	0.220	0.220

Table 3.6: Subsample Analysis

This table presents the results of our main regression on different subsamples. We use Spline Model 3 from Table 3.4 where we spline Term Loans and Credit lines using the three intervals—[0, 20), [20, 90), and [90, 100]. In Panel A, we show the regression results for subsamples constructed based on firm characteristics. In Panel B, we show the regression results for subsamples constructed based on country characteristics. In Panel C, we show the regression results for subsamples based on time periods: before, during, and after the global financial crisis. All columns include industry, country, and year fixed effects. In Panel A, Column (1) uses firms whose total assets in U.S. dollars are in the first tercile of all firms each year. Column (2) samples firms whose total assets in U.S. dollars are in the second tercile of all firms each year. Column (3) samples firms whose total assets in U.S. dollars are in the third tercile of all firms each year. Column (4) contains firms whose financial leverage is below the first tercile. Column (5) contains firms whose financial leverage is above the second tercile. Columns (6) and (7) compare firms whose asset tangibility is below the first tercile with firms whose asset tangibility is above the second tercile. Columns (8) and (9) compare firms with stocks listed in major U.S. exchanges to those without. In Panel B, Columns (1) and (2) contain firms from low-income and high-income countries by the World Bank's definition, respectively. Columns (3) and (4) compare firms from bank-based countries and market-based countries. Columns (5) and (6) compare firms incorporated in the U.S. and in the other countries. In Panel C, Columns (1)–(3) contain the regression results in the subperiods before 2007, between 2007 and 2011, and after 2011, respectively. Robust standard errors are clustered at the firm level. Industries are classified using 4-digit SIC code. t-statistics are presented in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Subsamples by firm characteristics

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	Small Firms	**Medium Firms**	**Large Firms**	**Low Leverage**	**High Leverage**	**Low Tangibility**	**High Tangibility**	**U.S. Listed Firms**	**Non-U.S. Listed**

									Firms
Term Loans [0, 20)	- 0.411***	- 0.445***	- 0.575***	-0.298**	-0.525***	-0.544***	-0.485***	- 0.942***	- 0.427***
	[-3.15]	[-4.02]	[-8.42]	[-2.51]	[-5.28]	[-5.41]	[-4.54]	[-7.39]	[-5.68]
Term Loans [20, 90)	0.0271	-0.0575	0.0347	-0.0697	0.0253	-0.148***	-0.0544	- 0.281***	-0.0527*
	[0.56]	[-1.46]	[1.29]	[-1.53]	[0.66]	[-3.98]	[-1.34]	[-5.17]	[-1.94]
Term Loans [90, 100]	1.202***	0.772***	0.800***	0.851***	0.776***	1.225***	1.107***	0.987***	1.354***
	[4.85]	[5.34]	[5.91]	[4.17]	[4.71]	[6.34]	[6.38]	[3.10]	[11.67]
Credit Lines [0, 20)	- 0.879***	- 0.310***	- 0.192***	-0.285**	-0.676***	-0.787***	-0.584***	- 1.035***	- 0.291***
	[-7.70]	[-3.77]	[-2.87]	[-2.55]	[-8.64]	[-8.63]	[-6.95]	[-8.57]	[-4.83]

Credit Lines [20, 90)	-0.0964*	-0.0525	0.0385	-0.215***	-0.136***	-0.222***	-0.0929*	- 0.503***	- 0.184***
	[-1.85]	[-1.13]	[0.93]	[-3.95]	[-3.02]	[-4.63]	[-1.92]	[-7.27]	[-5.64]
Credit Lines [90, 100]	1.713***	0.878***	1.246***	0.969***	1.704***	1.573***	1.557***	1.773***	1.635***
	[4.95]	[2.91]	[2.81]	[2.93]	[4.42]	[4.74]	[4.20]	[3.78]	[6.81]
Other Debt Types	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country, Industry, & Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	106,198	106,186	106,156	106,179	106,188	106,167	106,178	73,999	244,538

Adj. R^2	0.268	0.295	0.276	0.211	0.268	0.255	0.180	0.293	0.189

Panel B. Subsamples by Country Characteristics

	(1) High-Income Countries	(2) Low-Income Countries	(3) Bank-Based Countries	(4) Market-Based Countries	(5) U.S.	(6) Rest of World
Term Loans [0, 20)	-0.599***	-0.475***	-0.445***	-0.638***	-0.741***	-0.457***
	[-8.24]	[-4.02]	[-4.86]	[-6.99]	[-4.61]	[-6.45]
Term Loans [20, 90)	-0.119***	-0.023	-0.052	-0.168***	-0.319***	-0.047*
	[-4.18]	[-0.56]	[-1.62]	[-4.52]	[-4.94]	[-1.79]
Term Loans [90, 100]	0.714***	2.256***	1.289***	1.240***	0.711**	1.366***
	[5.78]	[11.11]	[9.88]	[6.06]	[1.98]	[11.94]

Credit Lines [0, 20)	-0.850***	-0.015	-0.141**	-0.988***	-1.187***	-0.285***
	[-13.08]	[-0.17]	[-1.97]	[-11.80]	[-8.42]	[-4.86]
Credit Lines [20, 90)	-0.149***	-0.267***	-0.227***	-0.189***	-0.444***	-0.203***
	[-4.29]	[-5.39]	[-5.65]	[-4.36]	[-5.60]	[-6.35]
Credit Lines [90, 100]	1.111***	2.254***	2.082***	1.366***	1.800***	1.678***
	[4.71]	[5.59]	[5.88]	[5.08]	[3.64]	[7.03]
Other Debt Types	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country,	Yes	Yes	Yes	Yes	Yes	Yes

Industry, & Year Fixed Effects						
N	205,704	112,834	185,058	133,482	54,682	263,853
Adj. R^2	0.242	0.211	0.196	0.252	0.309	0.189

Panel C. Subperiods

	(1)	**(2)**	**(3)**
	Before 2007	**2007–2011**	**2012–2018**
Term Loans [0, 20)	-0.585***	-0.472***	-0.647***
	[-5.50]	[-5.55]	[-6.45]
Term Loans [20, 90)	-0.012	-0.053*	-0.062
	[-0.30]	[-1.67]	[-1.53]
Term Loans [90, 100]	-0.106	0.665***	2.093***

	[-0.61]	[4.69]	[12.00]
Credit Lines [0, 20)	-0.998***	-0.675***	-0.287***
	[-10.52]	[-9.65]	[-3.36]
Credit Lines [20, 90)	-0.102**	-0.103***	-0.255***
	[-2.03]	[-2.71]	[-5.40]
Credit Lines [90, 100]	1.513***	1.305***	1.684***
	[3.91]	[4.49]	[5.42]
Other Debt Types	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Country, Industry, & Year Fixed Effects	Yes	Yes	Yes
N	66,345	96,058	156,138
Adj. R^2	0.255	0.246	0.214

Table 3.7: Channel Analysis

This table presents the results for our channel analysis. We use Spline Model 3 from Table 4 where we spline Term Loans and Credit lines using the three intervals—[0, 20), [20, 90), and [90, 100]. In Column (1), the dependent variable is asset growth rate from year t-1 to year t. In Column (2), it is return on assets, which is the ratio of net income over total assets. In Column (3), the dependent variable is total dividends over total assets. In Column (4), the dependent variable is cash and cash equivalents over total assets. In Column (5), the dependent variable is research and development expenditures over total assets. In Column (6), the dependent variable is capital expenditures over total assets. We use industry (classified using 4-digit SIC code), year, and country fixed effects in all columns. Robust standard errors are clustered at the firm level. t-statistics are in the brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variables:	**AGROW**	**ROA**	**DIV/TA**	**CASH/TA**	**R&D/TA**	**CAPEX/TA**
Term Loans [0, 20)	-0.003	-0.001	-0.016***	-0.055***	-0.004	0.006**
	[-0.28]	[-0.17]	[-9.29]	[-7.15]	[-0.54]	[2.20]
Term Loans [20, 90)	0.003	0.008***	0.0001	0.005*	0.005	0.004***
	[0.72]	[2.61]	[0.16]	[1.78]	[1.45]	[3.60]
Term Loans [90, 100]	0.043**	0.081***	0.021***	0.154***	-0.003	-0.003
	[2.15]	[6.03]	[7.97]	[11.61]	[-0.25]	[-0.64]
Credit Lines [0, 20)	-0.060***	0.101***	-0.001	-0.119***	-0.070***	-0.006**

	[-5.81]	[15.00]	[-0.48]	[-18.28]	[-10.48]	[-2.37]
Credit Lines [20, 90)	0.009	0.028***	-0.002**	-0.017***	-0.004	0.003**
	[1.62]	[7.87]	[-2.18]	[-4.83]	[-1.17]	[1.98]
Credit Lines [90, 100]	0.194***	0.030	0.050***	0.145***	0.062**	0.036***
	[4.99]	[1.27]	[7.37]	[6.02]	[2.31]	[4.08]
Senior Bonds	0.004	-0.041***	0.001	0.027***	0.010***	0.003***
	[0.93]	[-13.92]	[1.07]	[9.14]	[3.26]	[3.54]
Subordinated Bonds	-0.018**	0.002	-0.004***	0.045***	-0.008	0.001
	[-2.37]	[0.34]	[-4.63]	[6.36]	[-1.41]	[0.52]
Capital Leases	0.010**	0.001	0.002*	0.078***	0.028***	0.007***
	[2.13]	[0.31]	[1.73]	[21.49]	[6.69]	[6.05]
Commercial Paper	0.048***	-0.026***	0.009***	-0.059***	0.010	-0.000

	[4.09]	[-3.16]	[3.94]	[-7.39]	[1.57]	[-0.02]
Log(TA)	-0.007***	0.0316***	0.000***	-0.007***	-0.011***	0.000*
	[-16.05]	[67.16]	[3.72]	[-20.96]	[-25.68]	[1.69]
PPE/TA	-0.008**	0.0737***	0.000	-0.142***	-0.040***	0.077***
	[-2.08]	[23.78]	[0.52]	[-51.67]	[-11.36]	[60.02]
TD/TA	0.0297***	-0.022***	-0.001	0.017***	0.021***	0.001
	[10.43]	[-7.49]	[-0.91]	[6.71]	[7.56]	[0.91]
US List	0.312***	0.0771***	-0.00276	0.0415***	-0.018	0.104***
	[9.27]	[5.27]	[-0.70]	[2.78]	[-1.16]	[14.18]
GDP Growth	-0.061***	-0.023***	0.003***	-0.012***	0.0075***	-0.003***
	[-18.41]	[-12.65]	[9.29]	[-6.89]	[3.51]	[-4.19]

Log(GDP/CAP)	-0.087***	-0.061***	-0.0164***	-0.113***	0.003	-0.021***
	[-21.72]	[-21.23]	[-26.02]	[-39.17]	[0.88]	[-21.40]
Constant	0.709***	0.0861***	-0.0174***	0.360***	0.040*	0.056***
	[21.72]	[4.86]	[-4.33]	[20.45]	[1.81]	[7.03]
Country, Industry, & Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	318,543	316,889	203,953	295,742	108,483	287,492
Adj. R^2	0.068	0.257	0.235	0.314	0.383	0.272

CHAPTER 4. FOR BETTER OR WORSE? EVIDENCE FROM EXOGENOUS TURNOVER OF EXECUTIVES

Abstract

We address whether managers impact firm performance for better or worse, tackling three difficult empirical challenges. We employ exogenous external shocks that trigger managerial turnover to address identification concerns and provide plausible causal results. We analyze a single industry – banking – to avoid biases from unobserved or hard-to-control-for interindustry differences. We draw data from government-mandated reports for investigating channels with detail and accuracy not typically available from standard corporate finance datasets. We find managers strongly improve performance through channels of increased asset turnover and improved product quality, and these improvements are reflected in market values as well as accounting measures.

4.1. Introduction

The impact of executive managers of banking organizations on the performance of their corporations is of first-order importance for research and policy purposes. Modern banking organizations are difficult to manage because they require understanding of many other industries in the real economy as banks need to manage the risks of loans, deposits, off-balance sheet guarantees, and derivative contract services from firms across these industries. Bank management also demands understanding of the workings of financial markets that banks use to manage these risks[19] and the roles that financial institutions play in these markets. For this reason, the literature on the impact of executives typically excludes bank managers. In this paper, we fill the gap in the literature by focusing solely on bank executive managers issue and we exploit several additional research advantages that the banking industry and the available datasets that pertain to this industry afford.

The stakes for managerial mistakes in the banking industry are considerably outsized. Bank failures caused by managerial ineptitude may also threaten the soundness of the financial system. Michael Barr, Vice Chair for Supervision at the Federal Reserve, underscored this point in his congressional testimony on March 29, 2023, “I posit that every occurrence of a bank failure such as this [Silicon Valley Bank] clearly signifies a collapse in bank management...” Therefore, research on bank governance is necessary to prevent similar crises from happening in the future. Moreover, there are several advantages of conducting research on bank executives. First of all, many government-mandated reports provide much more detailed information on banks and banking holding companies than 10K and 8K reports filed by public firms. More importantly, these reports enable research on at all levels of financial conglomerates, the private subsidiary banks, parent companies, or the entire conglomerates which is generally impossible for non-financial private firms and business conglomerates. Lastly, as a result of stringent regulations, plausibly exogenous policy shocks are more and easier to find for banks, which can help to alleviate endogeneity concerns.

In this paper, we explore the extent to which top executives can significantly influence firm performance in a banking context via a particular governance mechanism – vertical managerial

[19] For example, banks need to purchase interest rate swaps from other financial institutions to hedge their interest risk exposure.

interlock. This refers to the practice where top executives from parent bank holding companies (BHCs) also occupy top executive roles at their subsidiaries (referred to as shared executives). Vertical managerial interlock is not uncommon in the business world. An example for corporations can be seen in the dual roles of Sundar Pichai as the CEO of both Alphabet Inc. and Google LLC. Our sample comprises 37 publicly traded bank holding companies, nearly half (17 out of 37) exhibited an overlap of at least one top executive between the parent holding company and their subsidiary commercial banks. We are the first to use this governance mechanism to study the influence of bank executives on bank performance. By employing innovative instrumental variables and government-mandated reports from privately owned commercial banks, we establish a causal relationship that illustrates the effects of bank executives on their operation outcomes.

Specifically, we use information on 350 large U.S. banks and the 114 bank holding companies (BHCs) that own them from regulatory reports unique to the banking industry. By way of background, most large U.S. banks are owned by BHCs, which may own multiple subsidiary commercial banks and other firms providing similar financial services. The executives in these BHCs in some cases serve in multiple roles among subsidiaries and headquarters. We employ data from ExecuComp to identify the bank and BHC executives and the capacities in which they serve within the organization, as well as bank Call Reports and other regulatory information sets for detailed financial data of banks and BHCs.

We address the identification issue using enforcement actions (EAs) against other bank subsidiaries within the same BHC, or against the BHC itself, as an instrumental variable for executive turnover at a given bank with no such actions against it. EAs are issued by government supervisors for violations of laws, rules, or regulations; unsafe or unsound practices; or breaches of fiduciary duty. These actions are shown in the literature to have important effects on the performance of the firms subject to them (e.g., Srinivas, Wadhwani, Ranjan, and Krishna, 2015; Delis, Staikouras, and Tsoumas, 2017 and 2019; Delis, Iosifidi, Kokas, Xefteris, and Ongena, 2020; Pereira, Malafronte, Sorwar, and Nurullah, 2019; Pugachev, 2019; Roman, 2020; Kleymenova, and Tomy, 2021; Berger, Cai, Roman, and Sedunov, 2022). An EA elsewhere in the BHC may cause executives of a given bank to be reassigned to the problem bank, reducing the number of executives at the bank for exogenous reasons unrelated to the performance of that bank. Thus, the managerial changes we examine are relatively free of the endogeneity problem associated with studying other managerial changes that are caused by performance issues at the same firm.

Our data cover all commercial banks in the U.S., and our sample includes private banks which are subsidiaries. This enables us to explore corporate governance of private firms and domestic subsidiaries which have rarely been studied due to data limitations. Also, our data has fine details on performance as well as outputs, costs, revenues, and product quality from Call Reports to enable us to assess the channels through which executives may affect performance. We measure performance three ways, return on assets (ROA), return on equity (ROE), and net interest margin (NIM). To assess the channels, we employ four different proxies for output quantities (two measures of loans, and one each for deposits and off-balance sheet activities), two proxies for cost efficiency (interest and noninterest expense ratios), a measure of asset turnover (interest income ratio), and a measure of product quality (nonperforming loans ratio). Comparable data are not available at the subsidiary level for most industries or from publicly available datasets such as 10-K annual reports or Compustat files. Thus, we measure the effects of executive turnover on performance as well as the channels for the performance changes in ways not typically possible in other studies.

The use of data from a single industry also avoids the confounding effects of interindustry differences in performance, technologies, and products noted above that may affect measured relations between firm performance and managerial changes. These banks have almost the same loan, deposit, and off-balance sheet products, employ similar technologies, and must use the same methods to compute their performance measures on their Call Reports, largely avoiding interindustry or even intra-industry measurement issues. We also include control variables and both firm and time fixed effects to mitigate the effects of other potential confounding differences in our sample.

By way of preview, our results suggest that executives matter to the extent that losing shared executives with parent BHCs significantly and negatively impact bank performance. The first stage IV analysis reveals that shared executives at a focal bank may be (re-)deployed to other EA-recipient banks within the same BHC. The second stage IV analysis shows that the performance of a focal bank significantly deteriorates after the departure of shared executives. Our three measures of performance, ROA, ROE, and NIM, all statistically and economically decline when a shared executive is moved from a given bank to elsewhere in the BHC after an EA is filed against the BHC itself or one of its BHC's other subsidiaries. Our channels analysis suggests that changes in output quantities and cost efficiency are not significant channels for the performance changes, but asset turnover and product quality are. When executives leave for exogenous reasons, the bank's interest income declines and its nonperforming loans increase.

Our brief additional investigations also provide some weak evidence that the other subsidiaries that receive the additional executives have improved performance using accounting-based measures, and that the performance of the BHC improves using a market-based measure. These additional findings should be viewed with more caution, as they are based on OLS regressions without the clean identification of causal effects of our main results. Finally, to address selection bias, we use propensity score matching and the Heckman selection model. For robustness, we add characteristics of the shared executives. The results of these additional tests are broadly consistent with our main results.

This paper proceeds as follows. Section 2 reviews the extant literature. Section 3 describes the data and methodology. Section 4 discusses the results, and Section 5 concludes.

4.2. Literature Review

Our paper directly contributes to the literature on executives and bank performance. This strand of literature focuses on executives of BHCs in the U.S., and empirical investigations in this literature shows that the ownership of non-CEOs significantly increases failure risk (Berger, Imbierowicz, and Rauch, 2016), and bank performance are better during the 2008 financial crisis if a bank has a chief risk officer (CRO) and the CRO reports to the CEO or directly to the board of directors whereas regular corporate governance measures such as CEO ownership do not make a significant impact (Aebi, Sabato, and Schmid, 2012). Our paper is closely related to Schaeck, Cihak, Maechler, and Stolz (2011). The authors use hand-collected data on executives of U.S. community banks, and they find that executives are more likely to be dismissed from risky institutions, but debtholders' stake in a bank or regulators' awareness of distress in a bank does not influence the dismissal of executives. Our paper completements their study by studying the departure of executives of commercial banks owned BHCs. Our instrument variable allows us to draw a plausibly causal relationship between bank executives and bank performance.

Our research contributes to a growing body of literature suggesting that managers can make significant contributions to firm outcomes. Bennedsen, Nielsen, Perez-Gonzalez, and Wolfenzon (2007) and Perez-Gonzalez (2006) find firm performance suffers when a successor CEO is a family member or other insider rather than outsider. Bertrand and Schoar (2003) find that manager fixed effects explain much of the variation in firm investment, financial and organizational decisions. An experiment by Bloom, Eifert, McKenzie, and Roberts (2013) suggests that management practices can improve productivity. Finally, Bennedsen, Perez-Gonzalez, and Wolfezzon (2020) find that firm performance declines when the CEO is hospitalized, and Johnson, Magee, Nagarajan, and Newman (1985) find that executive deaths are associated with abnormal positive stock price changes. Although managerial hospitalization and death are reasonably exogenous events, we argue that *EAs* against entities rather than people elsewhere in the BHC may offer even better identification because they originate in an entirely different firm. We also believe that our relatively clean focus on a single industry and our investigation of performance channels contribute significantly to this literature. Our results complement the work of Hale, Ployhart and Shepherd (2016) who find that bank branch performance declines following a turnover event, and recovery is slower after losing a manager (versus a non-manager employee). Our results are consistent with theirs, suggesting that performance suffers when a manager leaves.

Another large body of literature addresses the causes of managerial turnover. Campbell, Gallmeyer, Johnson, Rutherford, and Stanley (2011) find that there is an optimal level of CEO optimism and that boards are more likely to remove CEOs who are more or less optimistic. Huang, Maharjan, and Thakor (2020) suggest that forced turnover is more likely when investors disagree with managers. Cziraki and Groen-Xu (2020) find that the likelihood of turnover is related to the time remaining on the CEO's contract. Most of this literature focuses on the effects of firm performance on turnover. Weisbach (1988) finds that CEO turnover is related to performance, but that the strength of the relation differs with board independence. Numerous studies examine the effects of performance relative to a benchmark, rather than absolute performance. Warner, Watts, and Wruck (1988) find turnover is highly related to market-adjusted, rather than absolute firm performance. Morck, Schleifer, and Vishny (1989) find evidence consistent with industry wide performance being filtered out of turnover decisions. Barro and Barro's (1990) results suggest that bank CEOs are evaluated relative to their peers. However, two more recent papers suggest that absolute performance may also matter. Jenter and Kanaan (2015) find that CEOs are forced out following poor performance of the industry or market, despite the theoretical argument that boards should filter exogenous shocks. Fisman, Khurana, and Rhodes-Kropf (2014) find that turnover is more likely when stock price has fallen. In addition, a growing body of literature shows that corporate social responsibility (CSR) reduces turnover. For example, Carnahan, Kryscynski and Olson (2016) study the boundary conditions of this notion and argue that the effect of CSR on turnover is stronger for more meaningful SCR investments. We contribute to this literature with the first stage of our instrumental variable regression framework. Our use of *EAs* at other firms within the conglomerate may be viewed as an extension of the literature examining the causes of managerial turnover to a highly exogenous factor affecting turnover.

Our paper also contributes to a large body of literature on internal labor markets. Bidwell and Keller (2014) use data from investment banks to identify conditions under which positions are more likely to be filled internally. Belenzon and Tsolmon (2016) show that the ability of firms to redeploy workers across units varies with frictions in labor markets. Bidwell (2011) finds that workers promoted internally are initially more likely to be successful than external hires, and Groysberg, Lee, and Nanda (2008) find that firm-specific skills are an important determinant of future performance. McNeil, Niehaus, and Powers (2004) find that internal labor markets effectively discipline poor performance. Our paper differs from this as it focuses on the consequences of managerial turnover, and specifically when that turnover is prompted by an exogenous event.

At first blush, our results would seem to contradict those of Chauvin and Poliquin (2021) and Huneeus, Huneeus, Larrain, Larrain and Prem (2021). Both of these papers suggest that firms will optimally redeploy human capital away from business units in decline and into business units with better prospects. In other words, the manager is removed because performance is expected to decline. In this paper, we argue that performance declines because the manager is removed. However, because the managerial turnover events we observe are caused by an exogenous event, we believe that this is not a contradiction.

4.3. Data and Methods

Our data is gathered from four primary sources: ExecuComp for executive data, Y-9C reports from the Federal Bank of Chicago for BHC financial data, FFIEC Call Reports for commercial bank financial data, and bank supervisory agencies for data on enforcement actions (EAs). Our sample period spans from 2007-2017. ExecuComp implemented significant changes in reporting rules concerning executive titles in 2006, so we start in 2007 to ensure consistency in our main independent variable.

We begin with ExecuComp, which provides information on top executives' demographics, positions, and compensation in S&P 1,000 companies. When a top executive holds positions in both parent and subsidiary companies, the dataset specifies the subsidiary in the executive's title. We focus on executives at bank holding companies (BHCs) and their subsidiaries and restrict our analysis to BHCs in ExecuComp. We match BHCs in ExecuComp to Y-9C Reports and Call Reports to obtain financial data on their subsidiaries. Our final sample includes 1,595 firm-year observations for 350 unique subsidiary banks and 892 firm-year observations for 114 unique BHCs.

Table 4.1 Panel A shows the definitions of the variables in our analyses, and Panels B and C give summary statistics for the subsidiary bank and BHC variables, respectively.

4.3.1. Main Independent Variable

Our main independent variable is *#Shared Executives,* the number of executives of subsidiary banks who also serve in an executive capacity in the parent BHCs. Figure 4.1 shows the distribution of *#Shared Executives*. ExecuComp documents the subsidiary's name within the executive's title when they work for a subsidiary bank. For instance, if an executive's title is "Chairman of the Bank, CEO-Bank A," the individual serves as both the Chairman of the parent BHC and the CEO of Bank A, a subsidiary of the parent.

We manually extract potential subsidiary names from all BHC executives' titles to determine whether an executive works at a subsidiary. Next, we match these subsidiary names with bank names in Call Reports. To validate our matches, we ensure that the name and RSSD ID of each matched subsidiary commercial bank's upper-level holder match the parent BHC in ExecuComp. We then count the number of parent executives associated with each subsidiary bank, as depicted in Figure 4.1. When we conduct analyses at the BHC level, we aggregate this variable at the corresponding level. In our BHC-level analysis, we aggregate this variable accordingly. In this context, the main independent variable reflects the total number of parent executives holding top positions in any subsidiary banks. ExecuComp provides information on the CEO, CFO, and the three next highest-compensated executive officers in a company. Although the total number of executives may exceed five during CEO transition years, this occurrence is extremely rare in our sample.

The summary statistics in Table 4.1 Panel B and Figure 4.2 clearly indicate that most banks and BHCs in our sample do not share top executives. However, within the subset of banks that do share executives with their parent BHCs, the distribution of the number of shared executives is somewhat uniform, suggesting our analysis is not likely to be affected by clustered extreme values.

4.3.2. Dependent Variables

As noted, we use return on assets (*ROA*), return on equity (*ROE*), and net interest margin (*NIM*) to measure performance. For the channels, we proxy for output using measures from both sides of the balance sheet and off the balance sheet. We use commercial and industrial loans (*C&I loans*), commercial real estate loans (*CRE*), deposits, and total unused loan commitments, each scaled by gross total assets (*GTA*)[20]. Cost efficiency is captured by interest expense and noninterest expense, each scaled by *GTA*. Asset turnover is proxied by interest income divided by *GTA*, and product quality is measured by nonperforming loans (*NPL*) scaled by *GTA*. Our only market-based test is at the BHC level, for which we use the market-to-book ratios of parent BHCs.

4.3.3 Instrumental Variable

To address the endogeneity issue, we construct instrumental variables using enforcement action data obtained from federal banking agencies' websites. US bank supervisors periodically conduct off-site examinations of banks' Call Reports and on-site examinations as part of their monitoring responsibilities. When they identify unsafe or illegal practices, significant violations of laws, rules, or regulations, they can issue formal enforcement actions (*EA*s) against banks, BHCs, or their managers and publicly announce these actions (Roman, 2020). *EA*s against institutions, banks or BHCs, generally require recipients to meet specific financial ratio goals, such as raising the capital ratio above a safe level, or to abstain from engaging in unsafe or illegal activities. Roman (2016, 2020) shows that *EA*s have significant impacts on the risks and lending practices of recipient banks. Informal communications between bank regulators and examined banking firms before an *EA* is announced are not impossible. However, Berger, Cai, Roman, and Sedunov (2022) and Roman (2020) show that stock-market-based systemic risk measures and

[20] Gross total assets (GTA) equals total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve (a reserve for certain foreign loans). Total assets on Call Reports deduct these two reserves, which are held to cover potential, not incurred, credit losses. Therefore, GTA is a better representation of the value of a bank's assets.

valuations of borrowers of EA recipient banks are not affected until EAs are publicly announced, suggesting there is insignificant information leakage before the announcements. On the other hand, we do not use *EAs* against specific managers at these other institutions, as such actions may be less clearly linked to the movements of managers from other banks. We analyze the impact of different types of *EAs* on the number of shared executives, and we use the number of *EAs* against other banks in the same BHC of a focal bank, or against the BHC itself, as the instrument for managerial turnover at a bank with no *EA* against it. More details can be found in section 4.1.

This instrument meets the exclusion condition because *EAs* against other institutions clearly do not have a direct impact on the focal bank without an *EA*. Moreover, our instrument meets the relevant condition because in response to an *EA*, the parent BHC might reassign shared executives from the focal bank to the *EA* recipient bank or stop sharing executives with the focal bank while sharing more new executives with the *EA* recipient bank, leading to a decrease in the number of shared executives at the focal bank. The weak identification test reported in Panel A, Table 4.4 shows an F-statistic of 43.29 for our main specification, indicating our instrument is not irrelevant. In this setting, the instrument is relevant, but has no direct impact on the dependent variables, so both the exclusion and relevance conditions are met.

4.3.4. IV Regression Model

We include only two control variables because our analyses include very strong fixed effects for both firms and time periods, and our sample size is limited. We use bank size measured by log(GTA), and the *capital ratio* measured by equity divided by GTA as the control variables.

In our main analysis, we implement a two-stage instrumental variable regression as the following:

$First\ stage$:

$$\#shared\ Executives_{i,t-1} = \alpha_0 + \alpha_1 EA_{i,t-2} + \gamma CONTROLS_{i,t-1} + \mu_i + \mu_{t-1} + \varepsilon_{i,t-1}, \quad (1)$$

$Second\ stage$:

$$Y_{i,t} = \beta_0 + \beta_1 \#shared\ \widehat{Executives}_{i,t-1} + \delta CONTROLS_{i,t-1} + \mu_i + \mu_t + \sigma_{i,t}, \quad (2)$$

Where i is the index for banks, and t is the index for time. *EA* in equation (1) is our instrument variable, enforcement actions against other banks owned by the parent BHC of a given bank or against the BHC itself. $\#shared\ \widehat{Executives}_{i,t-1}$ is the predicted value of $\#shared\ Executives_{i,t-1}$. *Y* can be one of the outcome variables, including *ROA*, *ROE*, *NIM*, or each of the following scaled by *GTA*: *C&I loans*, *CRE*, *deposits*, *commits*, *interest expenses*, *non-interest expenses*, *interest income*, and *NPL*. *CONTROLS* is a vector of control variables, including log(*GTA*) and the *capital ratio*. The μ terms are bank and year fixed effects, and finally ε and σ are error terms. We first estimate equation (1) and compute $\#shared\ \widehat{Executives}_{i,t-1}$. Then, we use $\#shared\ \widehat{Executives}_{i,t-1}$ as our main independent variable in equation (2).

4.4. Empirical Results

In this section, we present the empirical results from our instrumental variable (IV) analysis, Heckman selection model, additional analyses, and BHC-level analysis. We will not discuss the results of the ordinary least squares (OLS) analysis, as they are not meaningful due to the three empirical issues previously mentioned.

The results of the IV analysis, which examines the impact of managerial changes on performance, are presented in Table 4.3. For the sake of completeness, we display each regression in three different ways: first, with only firm fixed effects; second, with only year fixed effects; and third, with both firm and year fixed effects. In all cases, our primary focus is on the most comprehensive specification, which includes both sets of fixed effects.

4.4.1. First Stage Analysis

We begin our instrumental variable analysis by investigating the association of *EAs* and our main independent variable, the number of shared executives, because the effect of *EAs* may vary depending on the type of recipient, thus, potentially leading to differential indirect influences on the number of shared executives between a focal bank and its parent BHC, and ex ante, we do not know which type of *EA* recipient matters the most. Therefore, we classify *EAs* into four categories based on the type of recipient (institutions or managers) and the level of the recipient in a bank conglomerate (at the BHC level or the subsidiary bank level): entity-related *EAs* of the BHC of a focal bank (*EA_Entity_Parent*), entity-related *EAs* of other subsidiary banks of the same BHC as a focal bank (*EA_Entity_OtherSub*), person-related *EAs* of the BHC of a focal bank (*EA_Person_Parent*), and person-related *EAs* of other subsidiary banks of the same BHC as a focal bank (*EA_Person_OtherSub*). These different types of *EAs* are exogenous to the number of shared executives between a focal bank and its parent BHC because the Federal Reserve issues enforcement actions to institutions or persons who violate laws and regulations or commit unsafe practices, and the focal bank is not the recipient of *EAs*, therefore, it is irrelevant to the *EAs*, otherwise, *EAs* will be issued to them directly. Nonetheless, there is a possibility that the shared executives between a focal bank and its parent BHC may be (temporarily) reassigned to the recipients of *EAs* to cope with the *EAs*. In other words, the different types of *EAs* we introduce above meet both the exclusion and relevance conditions, making them good candidates of instrumental variables for our main independent variable (see Figure 4.3 for an illustration). If it is true, a priori, we expect that entity-related *EAs* should be more relevant because entity-related *EAs* are issued as the results of the poor performance of a bank or a BHC whereas person-related

EAs are issued to bank professionals because of their wrongdoings which might not directly lead to negative consequences for their institutions. Figure 4 plots the number of each type of EAs and compares the number of each type of EAs with the number of shared executives. One may argue that the *EAs* against the parent BHC of a focal bank are not completely exogenous because a focal bank contributes to the performance of its parent BHC while under the influence of the parent BHC, especially when they share executives. However, if a focal bank plays a critical role in the unlawful or unsafe practices of the parent BHC, the focal bank should receive *EAs*, too. As for the possibility that *EAs* are issued against the shared executives, although our data could not offer a match between the *EA* recipients and the executives in our sample, we recognize that this measure can be endogenous as misconduct by a person can be the result of a corporate culture that prevails in the entire corporation, which may lead to poor performance and other negative consequences in the long run. Therefore, we refrain from using *EAs* against a person as our instrumental variable in our main analysis because of these concerns, even though we include it in the analysis in this section.

In Table 4.2, we present the ordinary least square regression analysis of the association between the number of shared executives and the four types of *EAs*, as well as the total number of *EAs* of the BHC of a focal bank (*EA_Parent*) and the total number of *EAs* of other subsidiary banks of the same BHC as a focal bank (*EA_OtherSub*). Column (1) in Table 4.2 shows the association between the total number of *EAs* received by the BHC of a focal bank and the number of the shared executives between them. The coefficient of the total number of *EAs* of the BHCs is negative but marginally insignificant. In Column (2) of Table 4.2, we distinguish entity-related *EAs* and person-related *EAs* at BHC level. The coefficients of both types of *EAs* are negative and significant. Interestingly, the magnitude and level of significance of entity-related *EAs* are larger than person-related *EAs*, suggesting that when there is an issue with the parent BHC of a focal bank, the BHC is very likely to retract its executives from the focal bank to address the issue. Meanwhile, if an executive of the BHC receives an *EA*, the BHC is less likely to reduce the number of shared executives with the focal bank, perhaps because executives are specialized in different fields and the shared executives may not be familiar with the field of the *EA* recipient at the BHC. We repeat the same analysis at the subsidiary level in Columns (3) and (4) in Table 4.2. Although the coefficient of the total number of *EAs* is negative and significant in Column (3), the effect is driven by the entity-related *EAs* of all other subsidiary banks of the same BHCs of focal banks because, in Column (4), the coefficient of entity related *EAs* of all other subsidiary banks are large in magnitude and statistically significant whereas the coefficient for person-related *EAs* is small and insignificant. The results from Columns (1)-(4) indicate that entity-related *EAs* at both levels are highly relevant to the number of shared executives, however, person-related *EAs* are not. We confirm our conjecture by inserting entity-related and person-related *EAs* at both BHC and subsidiary levels in the same regression, and the result is presented in Column (5) of Table 4.2. The coefficients of the two entity-related *EA* variables are both large and significant. In contrast, the coefficients of the two person-related *EA* variables are small and insignificant, which suggests that entity-related *EAs* are better instruments, and they are almost equally good. In Column (6), we run the analysis by adding the number of entity-related *EAs* of BHCs and other subsidiary banks. Although we are not surprised that the coefficient of the combined entity-related *EA* variable is negative and significant, we obtain an F-statistic that is the largest in all regressions in Table 4.2. This provides evidence that the combined entity-related *EAs* is the best instrument, and we will choose it as our instrument variable, and for the sake of brevity, we refer to this variable as *EA* in all the analyses below.

4.4.2. Two-stage Least Square Instrumental Variable Analysis

In this subsection, we discuss our instrumental variable analysis. Columns (1) to (3) of Table 4.3 contain the first-stage regression results for the effects of the *EA*, the instrument, on our main explanatory variable *#Shared Executives*. We find that more enforcement actions received by other subsidiary banks or the parent BHC reduces the number of shared executives in the focal bank, and the result is highly statistically significant except when firm fixed effects are excluded. This finding is consistent with our arguments above that those managers may be moved to help with problems elsewhere in the organization. The weak instrument test for the regression with both firm and year fixed effects yields an F-stat of 43.29, indicating our IV is not weak.

Columns (4) to (12) of Table 4.3 present the second-stage results, with columns (4) to (6) showing *ROA* results, followed by *ROE* in columns (7) to (9) and *NIM* in (10) to (12). We again focus on the most complete specifications with the full fixed effects. In all of these full specifications, the coefficients are positive and statistically significant, suggesting that managers matter to performance – reductions in managers because of *EAs* elsewhere in the organization decrease predicted performance. We also find the relations between the number of shared executives and three performance measures are economically significant: for a bank with median performance, a one-unit drop in the number of shared executives corresponds to a 62.5% reduction in *ROA*, an 87.0% reduction in *ROE*, and a 33.3% reduction in *NIM*. We are not surprised that the size of the effects is large because of the local treatment effect (Jiang, 2017)[21].

We next investigate the channels through which changes in performance may occur in Table 4.4. We study four types of channels: output quantity, cost efficiency, asset turnover and output quality. In Columns (1) to (4), we show the IV regression results for four different types of

[21] In additional untabulated results, we examine how long the effects of the number of shared executives last and do not find consistent results.

outputs. They are commercial and industrial loans, commercial real estate loans, deposits, and unused loan commitments (each scaled by gross total assets). The coefficients of the number of shared executives are insignificant in the four regressions, suggesting that managers do not improve performance through changing output levels. Columns (5)-(7) show the IV regression results for interest expenses, non-interest expenses, and total expenses measures of cost efficiency. Although the coefficients of the predicted number of shared executives are positive and significant in Column (5), suggesting costs increase with the number of shared executives, the coefficient in Column (7) is both insignificant and small which implies that this deterioration in cost efficiency may not matter to firm performance. As for the asset turnover channel, we find a positive and significant effect on interest income in column (8), suggesting that improved performance can be achieved by earning more interest per dollar of gross total assets, given that interest income is essentially the bank equivalent of sales. In Column (9), we show the result for nonperforming loans, an inverse measure of product quality, given that high quality loans are less likely to be in arrears. The negative and significant coefficient in this column suggests that managers may positively affect performance through improved product quality. In sum, our findings suggest that managers may most likely improve firm performance through increased asset turnover and better product quality, rather than through increased output or cost reductions.

4.4.3. Selection Bias

We consider potential selection bias in this section. It is possible that in our sample, the banks that share executives with their parent BHCs are systematically different from other banks, or that their choice of sharing executives is not random. We address this issue by implementing the Heckman selection model[22]. At the first stage of the Heckman selection model, we regress

[22] Another common practice to address selection bias is propensity score matching (PSM). PSM identifies untreated banks that are very similar to the treated banks then estimates the treated effect on the matched sample. However,

whether subsidiary banks have one or more shared executives with their parent BHCs, and in the second stage, we estimate the effect of the shared executives to the performance of subsidiary banks. In Table 4.5, we present the results of the Heckman selection model. The results are consistent with our IV analysis but weaker. Moreover, the reverse mills ratio is insignificant, which implies that sample selection bias might not be a concern. We are not surprised to find weaker results in these regressions because the Heckman selection model does not address the simultaneity issue that also contaminates our estimation.

4.5. Additional Test

In the previous sections, we show that when a focal bank's BHC or other banks owned by the BHC receive enforcement actions, the number of shared executives between the BHC and the focal bank will be reduced, and vice versa. Moreover, the change in the number of shared executives has a prominent effect on the performance of the focal bank. If the results are robust, then we should expect to observe greater improvements in the performance of a subsidiary bank when some of the shared executives have worked in the banking industry before they become shared executives. This is because these executives understand the operation of banks and thus should offer greater benefit to the subsidiary bank. To test this hypothesis, we construct a dummy variable equaling one if at least one of the shared executives at the bank level worked in the banking industry one year before they become shared executives at the focal subsidiary banks. We test our hypothesis using an instrumental variable analysis. The results are presented in Table 4.6.

Columns (1) and (2) show the two first-stage regressions. The coefficients of the interaction of *EA* and the two main effects are highly significant, and the F-stats are 63.81 and 23.43, demonstrating that our instruments are strong. In columns (2)-(14), we run the same regressions

PSM is not practical for our case because, due to a restricted sample size, it is hard to find sufficient number of such similar but untreated banks, leading to a lack of statistical power in the estimation stage.

as the second-stage analysis in Tables 3 and 4 with the predicted interaction of *EA* and *InBank*. We find the signs of the coefficients of the interaction variable are highly consistent with the previous results and the levels of significance become even stronger. Surprisingly, the coefficients for the number of shared executives are of the opposite sign. This indicates that the effects of the number of shared executives we observe in the previous sections are actually driven by the interaction term, and the effects of the variable itself turn out to be opposite. This means that only those shared executives with banking experience can improve the performance of subsidiary banks. The results of this additional test not only reveal a channel of the effect of shared executives, but also illustrate that the casual relationship between executives and firm performance is robust because if it were spurious, then the past experience of executives should not matter.

To show the robustness of these results, we also analyze a number of characteristics of the shared executives. The extant literature demonstrates that characteristics of top executives, such as tenure, age, gender, power, and incentives, can have substantial influence on their effectiveness. We use average tenure, average age, the ratio of female executives, a dummy variable indicating if a CEO presents in the shared executives, and average compensation to measure these characteristics, respectively. We examine the effects of these characteristics both separately and simultaneously, and the results are shown in the Appendix. Panels A to E report the instrument variable analysis results for each of the characteristics. Columns (1) and (2) in each panel report the F-stats for the first stage regression. Most of them are small, indicating that the instruments are weak, except for the incentives for the shared executives. The results in Panels A to E show that the coefficients of the aforementioned characteristics and the interaction terms of each of them with the number of shared executives are generally insignificant, suggesting that these characteristics do not play an important role.

4.6. BHC level analysis

We report the results in Table 4.7. The coefficient on *#Shared Executives_BHC* is uniformly positive and statistically significant. The coefficient of 0.004 in the full specification suggests an increase in market value of roughly $14 million, for an average sized BHC in our sample of about $3.5 billion market value, from adding an additional executive to a subsidiary bank. This result could reflect the ability of BHC executives in improving a subsidiary bank's performance, an improvement in communications between parent BHCs and their banks, or attenuation of a managerial agency problem. Our data do not allow investigation of the channels behind this final finding, and we finally again emphasize that the identification of causal effects is not very strong. Nonetheless these results are consistent with the rest of our results and suggest that managers matter.

4.7. Conclusion

We find strong evidence that managers affect firm performance using data on bank holding companies and their subsidiary commercial banks. These data allow us to effectively take on three difficult empirical challenges that are present in the standard corporate setting of identification using exogenous shocks, unobserved interindustry differences, and lack of sufficiently detailed data to assess performance channels. We find that performance changes follow changes in management and that such changes are realized primarily through asset turnover and product quality rather than increased output or decreased costs. Finally, we find that a market-based measure of performance for the BHC also improves when accounting-based measures of performance improve among the subsidiaries. Further tests suggest that our results are robust and are not driven by selection bias.

We close by addressing whether these advantages in addressing econometric challenges are sufficient to offset any concern over whether our findings from this one industry are likely to generalize to the broader corporate setting. Banks operate in a regulated industry and the nature of their products differs from that of most other industries, nonetheless large U.S. banking organizations are corporations that act in the interests of shareholders and other corporate stakeholders in essentially the same fashion as any firm producing outputs for profit. Thus, we suggest that the effects of managers on performance in the banking industry are likely not that different from such effects elsewhere. We encourage other research using comparable detailed datasets on other industries to corroborate or contradict our findings.

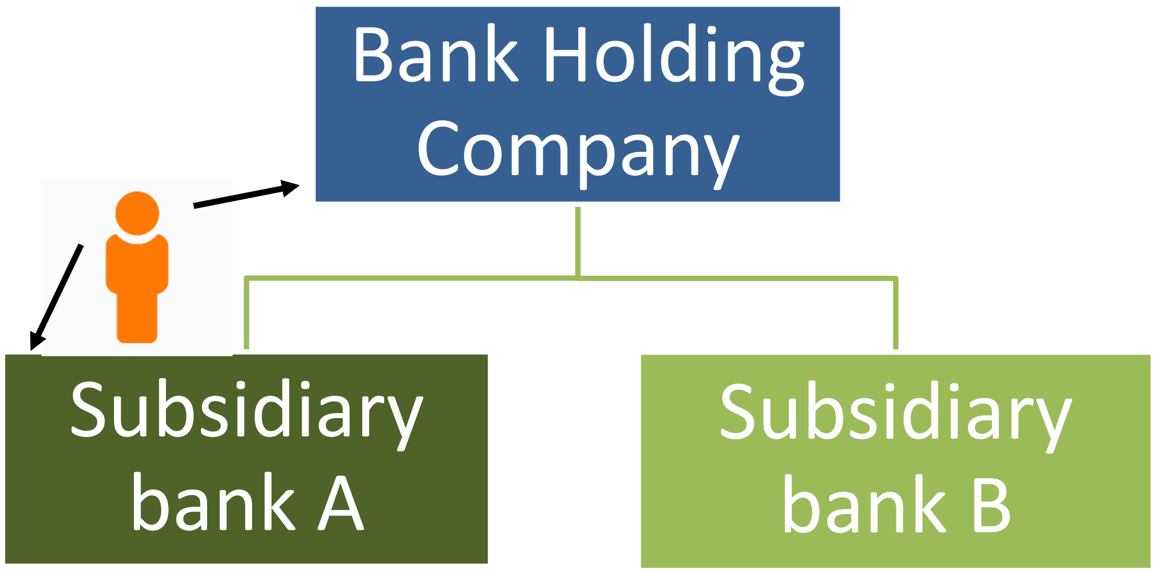


Figure 4.1. Shared Executives.

This figure illustrates an example of shared executives. The blue rectangle represents a parent bank holding company (BHC), and the grey boxes represent two subsidiary banks of the BHC. The orange person represents a manager who holds top executive positions in both the BHC and subsidiary bank A represented by the darker grey box.

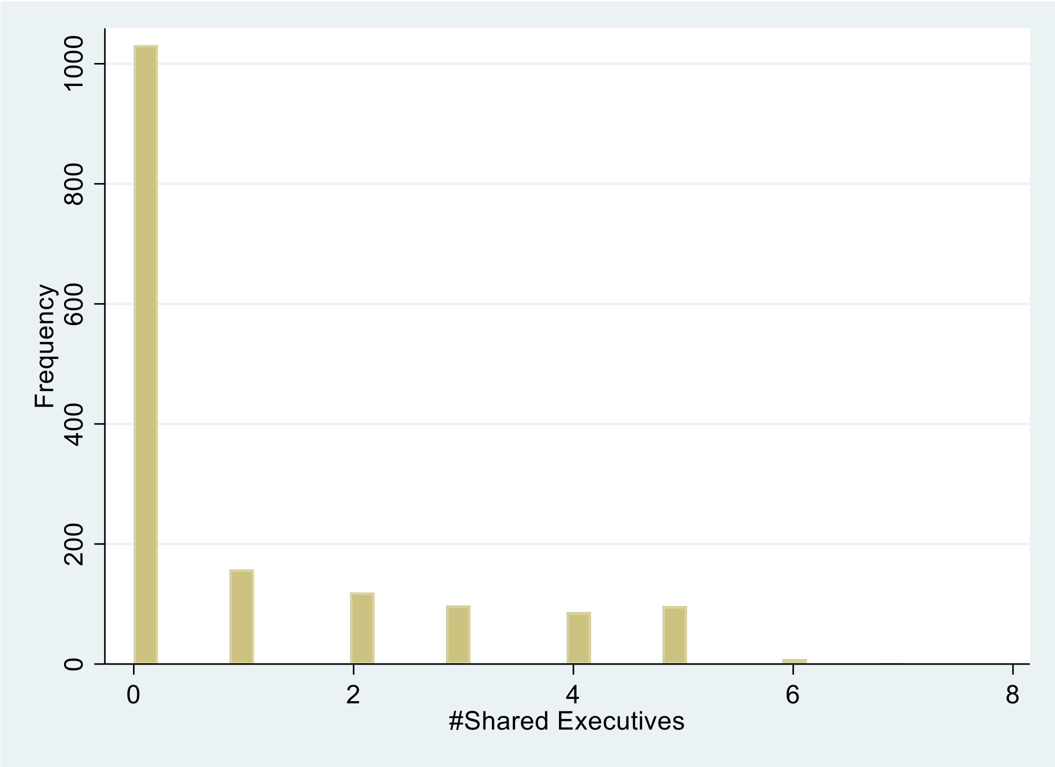


Figure 4.2. **Distribution of Shared Executives**.

This figure shows the frequency distribution of the number of shared executives between bank holding companies and their subsidiary banks at the subsidiary level.

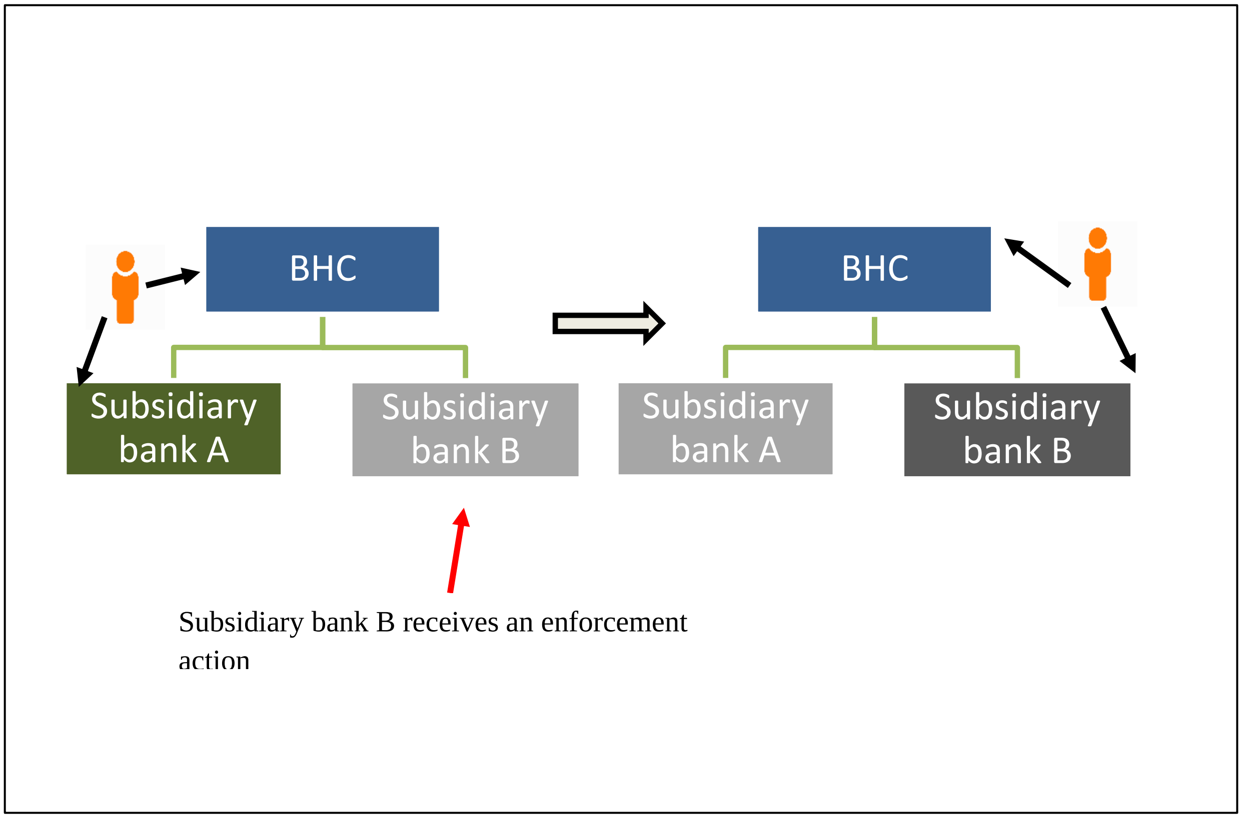


Figure 4.3. Empirical Setting.

This figure illustrates an example of shared executives being moved to another subsidiary bank in response to an enforcement action. The blue indicates a parent bank holding company (BHC), and the grey boxes represent two subsidiary banks of the BHC. The orange person represents a manager. In the beginning, this person takes top executive positions at the BHC and subsidiary bank A. At some point in time, another subsidiary of the BHC, subsidiary bank B, receives an enforcement action against the bank. So, the BHC moves the executive from subsidiary bank A to subsidiary bank B.

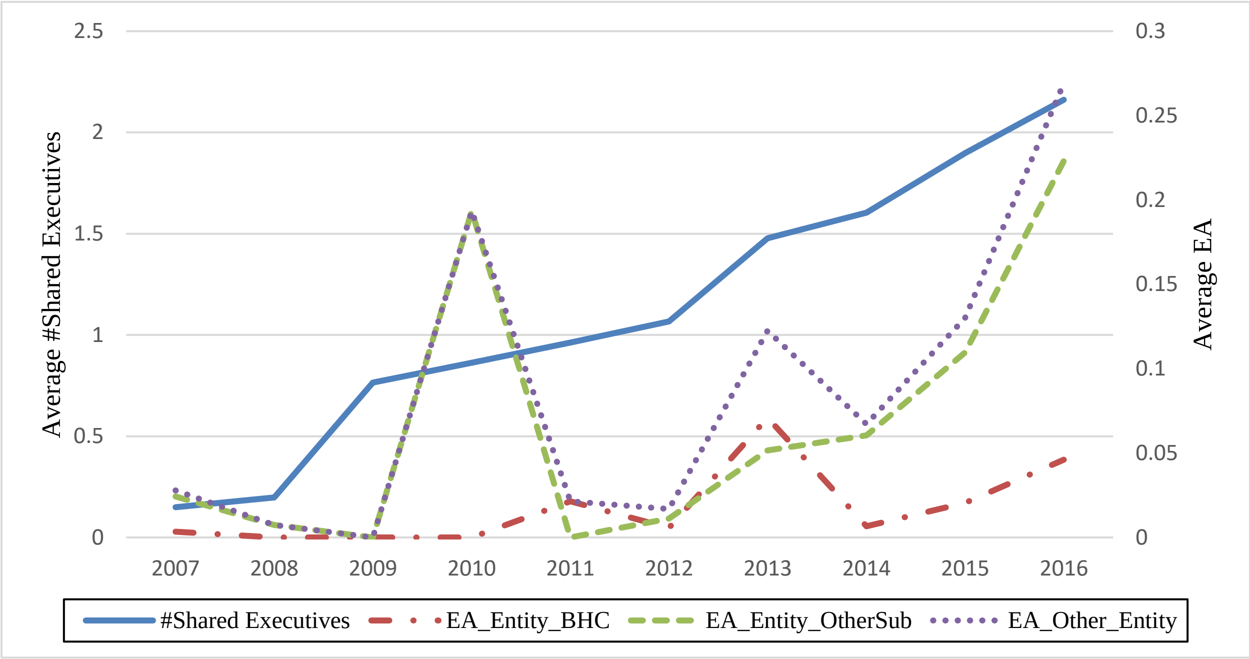


Figure 4.4. Enforcement Actions and Shared Executives.

This figure shows the Average #Shared Executives and Average EA.

Table 4.1: Variable Definitions and Summary Statistics

This Table presents definitions and summary statistics for all variables in our analysis. Panel A lists variable definitions, Panel B displays the summary statistics for the bank sample, and Panel C shows the summary statistics for the bank holding company (BHC) sample.

Panel A: Variable Definitions

Variable	Definition
Performance variables	
ROA	Return on assets, calculated as net income divided by GTA (GTA). GTA is defined below.
ROE	Return on equity, calculated as net income divided by total equity.
NIM	Net interest margin, calculated as net interest income divided by GTA.
Channel variables	
C&I Loans	Commercial and industrial loans.
CRE	Commercial real estate loans.
Deposits	Total deposits.
Commitments	Total unused loan commitments.
Interest expenses	Total interest expenses.
Non-interest expenses	Total non-interest expenses.
Interest income	Total interest income.
NPL	Total non-performing loans.
Key explanatory variable	
#Shared Executives	The number of executives shared between a parent bank holding company and its subsidiaries.
Instrumental Variable	
EA	The number of enforcement actions against other banks or the parent BHC of a focal bank.
Control Variables	
GTA	Gross total assets, equals to the sum of total assets, the allowance for loan and lease losses, and the allocated transfer risk reserve.
Log(GTA)	Natural logarithm of GTA.
Capital Ratio	Total equity divided by GTA.
Additional Bank Holding Company (BHC) variables	

MTB	The market value of equity plus the book value of assets minus the book value of equity divided by the book value of assets.
#Shared Executives_BHC	The number of BHC executives shared with all its subsidiary banks.

Panel B: Bank Variables Summary Statistics

	Count	**Mean**	**Std.**	**25%**	**50%**	**75%**
ROA	1595	0.005	0.013	0.003	0.008	0.011
ROE	1595	0.038	0.136	0.027	0.069	0.099
NIM	1595	0.029	0.008	0.026	0.030	0.034
C&I Loans	1595	0.120	0.087	0.055	0.107	0.171
CRE	1595	0.344	0.250	0.162	0.280	0.469
Deposits	1595	0.773	0.078	0.729	0.788	0.831
Commits	1595	0.127	0.096	0.049	0.104	0.187
Interest Expenses	1595	0.008	0.007	0.003	0.005	0.012
Non-Interest Expenses	1595	0.026	0.010	0.020	0.025	0.030
Interest Income	1595	0.037	0.011	0.031	0.038	0.045
NPL	1595	0.021	0.021	0.007	0.013	0.028
#Shared Executives	1595	0.981	1.601	0.000	0.000	2.000
EA	1595	0.083	0.502	0.000	0.000	0.000
Log(GTA)	1595	15.041	1.847	13.619	15.118	16.282
Capital Ratio	1595	0.116	0.053	0.089	0.106	0.128
Panel C: BHC Variables Summary Statistics						
MTB	784	1.033	0.050	0.998	1.027	1.061
#Shared Executives_BHC	784	1.7	1.9	0.0	1.0	3.0
Log(GTA)	784	15.92	1.580	14.66	15.73	17.04
Capital Ratio	784	0.093	0.042	0.074	0.087	0.106

Table 4.2: The Effects of Enforcement Actions on the Number of Shared Executives-OLS Analysis

This table shows the regression results for the effect of different types of enforcement actions against either/both other subsidiary banks owned by the parent bank holding companies of the focal banks or/and the parent bank holding companies on the number of shared executives between the focal banks and their parent bank holding companies. Column (1) shows the effect of all enforcement actions on parent bank holding companies (EA_Parent) on the number of shared executives. Column (2) shows the effects of the enforcement actions on parent bank holding companies against entities and against person (EA_Entity_Parent and EA_Person_Parent, respectively) on the number of shared executives. Column (3) shows the effect of all enforcement actions on other subsidiary banks of the parent bank holding company of the focal banks (EA_OtherSub) on the number of shared executives. Column (4) shows the effects of the enforcement actions on other subsidiary banks of the parent bank holding company of the focal banks against entities and against person (EA_Entity_OtherSub and EA_Person_OtherSub, respectively) on the number of shared executives. Column (5) shows the effects of EA_Entity_Parent, EA_Person_Parent, EA_Entity_OtherSub and EA_Person_OtherSub on the number of shared executives. Column (6) shows the effect of the enforcement actions against entity and person on both the parent bank holding company of the focal banks and other subsidiary banks owned by the parent bank holding companies (EA_Other_Entity) on the number of shared executives. The sample period is from 2007 to 2017. *, **, and *** denote significance at 10%, 5%, and 1% level.

Dependent Variable:	**(1) #Shared Executives**	**(2) # Shared Executives**	**(3) # Shared Executives**	**(4) # Shared Executives**	**(5) # Shared Executives**	**(6) # Shared Executives**
EA_Parent	-0.099					
	(-1.54)					
EA_Entity_Parent		-0.283***			-0.143**	
		(-3.44)			(-2.25)	
EA_Person_Parent		-0.053*			-0.015	
		(-1.90)			(-0.77)	
EA_OtherSub			-0.091***			
			(-3.78)			
EA_Entity_OtherSub				-0.203***	-0.187***	
				(-6.34)	(-6.10)	
EA_Person_OtherSub				-0.024	-0.028	
				(-1.28)	(-1.46)	
EA_Other_Entity						-0.185***
						(-6.58)
log(GTA)	0.277	0.274	0.276*	0.276	0.257	0.255
	(1.65)	(1.63)	(1.67)	(2.05)	(1.55)	(1.53)
Capital Ratio	2.030	2.013	2.045	1.978	1.974	1.958

	(1.38)	(1.37)	(1.38)	(1.33)	(1.33)	(1.32)
Constant	-3.417	-3.356	-3.386	-3.129	-3.092	-3.065
	(-1.32)	(-1.29)	-1.32	(-1.22)	(-1.20)	(-1.19)
Adj. R^2	0.684	0.684	0.685	0.686	0.686	0.687
N	1,553	1,553	1,553	1,553	1,553	1,553
F	2.2	4.3	6.38	16.0	11.0	20.1
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.3: Do Managers Influence Firm Performance for Better or Worse? - Instrumental Variable Analysis

This table shows the regression results of the impact of the number of shared executives (#Shared Executives) on firm profitability using an instrumental variable (IV) approach. Our instrument is the number of enforcement actions (EAs) against other subsidiary banks owned by the same BHC as the focal bank or against the BHC itself. Columns (1) to (3) present the first-stage IV regression results using different sets of fixed effects– bank only, Time only, and both. Columns (4) to (12) contain the second-stage IV regression results for different measures of profitability with the same sets of fixed effects. Columns (4) to (6) contain the regression results with ROA as the dependent variable while columns (7) to (9) and columns (10) to (12) display the findings for ROE and net interest margin (NIM) as the dependent variables, respectively. We only show adjusted R^2s for the first-stage regressions because adjusted R^2 is meaningless in the second-stage regressions. F-Statistics reported are the statistics for weak identification test. The sample period is from 2007 to 2017. *, **, and *** denote significance at 10%, 5%, and 1% level.

	First Stage			Second Stage								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Dependent Variable:	**#Shared Executives**	**#Shared Executives**	**#Shared Executives**	**ROA**	**ROA**	**ROA**	**ROE**	**ROE**	**ROE**	**NIM**	**NIM**	**NIM**
EA	-0.032*	-0.389***	-0.186***									
	(-1.69)	(-7.39)	(-6.63)									
$\#\widehat{Shared\ Exec}$				-0.012	0.002*	0.005**	-0.047	0.033**	0.060**	0.083	0.005**	0.010***
				(-0.75)	(1.75)	(2.15)	(-0.32)	(2.36)	(2.28)	(1.61)	(2.40)	(3.31)
log(GTA)	1.011***	0.181***	0.248	0.014	-0.000	-0.007***	0.064	-0.007*	-0.069***	-0.084	-0.001**	0.002
	(6.44)	(4.33)	(1.49)	(0.89)	(-1.13)	(-3.37)	(0.43)	(-1.66)	(-3.26)	(-1.60)	(-2.30)	(0.98)
Capital Ratio	4.945***	-1.441*	1.958	0.045	-0.000	-0.066**	-0.023	-0.262*	-0.762***	-0.409	-0.011	-0.001
	(3.50)	(-1.80)	(1.31)	(0.55)	(-0.01)	(-2.52)	(-0.03)	(-1.68)	(-3.34)	(-1.51)	(-1.18)	(-0.07)
Adj. R^2	0.636	0.202	0.687									
N	1553	1593	1553	1553	1593	1553	1553	1593	1553	1553	1593	1553
F-Statistic	2.85	54.69	43.29									
Bank FE	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes
Time FE		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes

Table 4.4: Channels Through Which Managers May Matter to Firm Performance-Instrumental Variable Analysis

This table presents the results of instrumental variable (IV) regression results for our channel analysis. Our instrument is the number of enforcement actions (EAs) against other subsidiary banks owned by the same BHC as the focal bank or against the BHC itself. Columns (1) to (4) show the results for the output quantity channel. Column (1) shows the result of IV regression with commercial and industrial loans (C&I loans) as the dependent variable. Column (2) shows the result of IV regression with commercial real estate loans (CRE) as the dependent variable. Column (3) shows the result of IV regression with total deposits as the dependent variable. Column (4) shows the result of IV regression with total unused loan commitments as the dependent variable. Columns (5) to (7) show the results for the cost efficiency channel. Column (5) shows the result of IV regression with interest expenses as the dependent variable. Column (6) shows the result of IV regression with non-interest expenses as the dependent variable. Column (7) shows the IV regression result of total expenses as the dependent variable. Columns (8) and (9) show the IV regression results of the output quality channel with interest income and non-performing loans (NPL) as the dependent variables, respectively. All dependent variables are scaled by GTA. We only show adjusted R^2s for the first-stage regressions because adjusted R^2 is meaningless in the second-stage regressions. The sample period is from 2007 to 2017. *, **, and *** denote significance at 10%, 5%, and 1% level.

	Output Quantity				Cost Efficiency			Asset Turnover	Output Quality
Dependent Variable:	**(1) C&I Loans/GTA**	**(2) CRE/GTA**	**(3) Deposits/GTA**	**(4) Commitments/GTA**	**(5) Interest Expenses/GTA**	**(6) Non-Interest Expenses/GTA**	**(7) Total Expenses/GTA**	**(8) Interest Income/GTA**	**(9) NPL/GTA**
$\#\widehat{Shared\ Execu}$	0.003	-0.014	-0.008	-0.025	0.003**	0.003	0.006	0.013***	-0.011**
	(0.44)	(-0.69)	(-0.88)	(-1.47)	(2.53)	(0.94)	(1.52)	(3.15)	(-2.53)
log (GTA)	0.036***	0.011	-0.016*	0.019*	0.000	0.003**	0.003	0.002	0.009***
	(3.91)	(0.66)	(-1.83)	(1.92)	(0.25)	(2.26)	(1.72)	(0.96)	(2.93)
Capital Ratio	0.088	-0.053	-0.052	0.039	-0.022*	0.067***	0.045**	-0.023	0.012
	(1.30)	(-0.22)	(-0.70)	(0.38)	(-1.88)	(4.56)	(2.09)	(-0.91)	(0.60)
N	1553	1553	1553	1553	1553	1553	1553	1553	1553
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.5: Is the Managers' Influence Driven by Selection Bias? -Selection Bias Analysis This table contains the results of the Heckman selection model. Column (1) shows the result for the first stage of the Heckman selection model. The dependent variable is a dummy variable which equals to one if the number of shared executives between a subsidiary bank and its parent BHC is greater than zero and equals to zero otherwise. Columns (2) to (4) show the results for profitability. We measure profitability using ROA in Column (2), ROE in Column (3), and net interest margin (NIM) in Column (4). Columns (5) to (8) show the results for the output quantity channel. We measure Output using commercial and industrial loans (C&I loans) in Column (5), commercial and real estate loans (CRE) in Column (6), deposits in Column (7) and unused loan commitments (commitments) in Column (8). Columns (9) to (11) show the results for the cost efficiency channel. We measure costs using interest expenses in Column (9), non-interest expenses in Column (10), and of total expenses in Column (11). Columns (12) and (13) show the result of the output quality channel with interest income and non-performing loans (NPL) as the dependent variables, respectively. All dependent variables in Columns (5) to (13) are scaled by gross total assets (GTA). The sample period is from 2007 to 2017. *, **, and *** denote significance at 10%, 5%, and 1% level.

	First Stage	**Profitability**			**Output Quantity**				**Cost Efficiency**			**Asset Turnover**	**Output Quality**
Dependent Variable:	**(1) Shared Dummy**	**(2) ROA**	**(3) ROE**	**(4) NIM**	**(5) C&I Loans/GTA**	**(6) CRE/GTA**	**(7) Deposits/GTA**	**(8) Commitments/GTA**	**(9) Interest Expenses/GTA**	**(10) Non-Interest Expenses/GTA**	**(11) Total Expenses/GTA**	**(12) Interest Income/GTA**	**(13) NPL/GTA**
EA	-0.253**												
	(-2.24)												
#Shared Executives		0.001*	0.007**	0.000	-0.001	-0.011***	-0.001	0.001	-0.000**	0.000	0.000	-0.000	-0.001***
		(1.73)	(2.25)	(1.24)	(-1.31)	(-3.78)	(-0.72)	(0.29)	(-2.22)	(1.42)	(0.66)	(-0.04)	(-3.33)
log(GTA)	0.306***	-0.009***	-0.100***	0.001*	0.010	0.018	-0.000	0.025**	0.001***	0.001	0.003**	0.004***	0.016***

	(16.56)	(-4.08)	(-4.83)	(1.75)	(1.57)	(0.92)	(-0.01)	(2.10)	(3.55)	(1.00)	(2.12)	(4.63)	(5.29)
Capital Ratio	-1.747**	-0.032	-0.498**	0.031***	0.151**	-0.615***	-0.179	0.129	-0.033***	0.092***	0.060***	-0.003	-0.170***
	(-2.10)	(-1.44)	(-2.26)	(3.52)	(2.27)	(-2.90)	(-1.34)	(1.03)	(-7.70)	(7.13)	(4.57)	(-0.42)	(-5.33)
N	1914	1914	1914	1914	1914	1914	1914	1914	1914	1914	1914	1914	1914
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.6: Do Managers with Past Banking Experience Have a Stronger Influence? -Additional Instrumental Variable Analysis

This table displays the results of additional analysis of the interaction effect of the number of shared executives (#Shared Executives) and their past banking experience (InBank). InBank equals one if there is at least one shared executive who has worked in the banking industry before they become shared executives. Columns (1) and (2) show the results for the two first-stage regressions. Columns (3)- (14) show the second stage results. We measure profitability using ROA in Column (3), ROE in Column (4), and net interest margin (NIM) in Column (5). Columns (6) to (9) show the results for the output quantity channel. We measure Output using commercial and industrial loans in Column (6), commercial and real estate loans (CRE) in Column (7), deposits in Column (8) and unused loan commitments (commitments) in Column (9). Columns (10) to (12) show the results for the cost efficiency channel. We measure costs using interest expenses in Column (10), non-interest expenses in Column (11), and total expenses in Column (12). Columns (13) and (14) show the result of the asset turnover channel with interest income and non-performing loans (NPL) as the dependent variables, respectively. In Panel B, Columns (1) and (2) show the results for the two first-stage regressions. Columns (6) – (14) are scaled by gross total assets (GTA). The sample period is from 2007 to 2017. *, **, and *** denote significance at 10%, 5%, and 1% level.

	First Stage		**Profitability**			**Output Quantity**				**Cost Efficiency**			**Asset Turnover**	**Output Quality**
Dependent Variable:	**(1) #Shared Executives**	**(2) #Shared Executives *InBank**	**(3) ROA**	**(4) ROE**	**(5) NIM**	**(6) C&I Loans/ GTA**	**(7) CRE/ GTA**	**(8) Deposits/ GTA**	**(9) Commitments/GTA**	**(10) Interest Expenses/ GTA**	**(11) Non-Interest Expenses/ GTA**	**(12) Total Expenses/ GTA**	**(13) Interest Income/ GTA**	**(14) NPL/ GTA**
EA	-1.176***	-0.510***												
	(-11.28)	(-4.89)												
EA*InBank	0.988***	0.322***												

	(-10.76)	(-3.50)												
#$\widehat{Share}$ Executives *InBank			0.060***	0.648***	0.025***	-0.029**	-0.238***	-0.052***	-0.029	0.002	0.000	0.002	0.025***	-0.076***
			(14.07)	(14.79)	(4.49)	(-2.41)	(-6.20)	(-3.37)	(-0.95)	(0.91)	(0.06)	(0.33)	(3.48)	(-10.12)
#$\widehat{Share}$ Executives			-0.055***	-0.589***	-0.014***	0.032***	0.224***	0.044***	0.004	0.001	0.002	0.004	-0.012***	0.066***
			(-24.89)	(-26.37)	(-5.31)	(4.69)	(9.53)	(5.57)	(0.27)	(1.14)	(1.02)	(1.15)	(-3.45)	(17.21)
InBank	-2.390***	-0.723***	-0.045***	-0.533***	-0.018***	0.040***	0.190***	0.017**	0.007	-0.001	-0.006***	-0.007***	-0.018***	0.045***
	(-17.63)	(-5.34)	(-20.83)	(-26.13)	(-7.27)	(5.21)	(8.52)	(1.99)	(0.48)	(-1.20)	(-2.95)	(-2.67)	(-5.50)	(12.46)
log(GTA)	0.241	0.239	-0.006***	-0.064***	0.002	0.035***	0.009	-0.016*	0.019*	0.000	0.003**	0.003*	0.003	0.008***
	(1.46)	(1.44)	(-3.24)	(-3.14)	(1.05)	(3.90)	(0.56)	(-1.91)	(1.92)	(0.25)	(2.23)	(1.73)	(1.01)	(2.83)
Capital Ratio	2.053	2.02	-0.066**	-0.757***	-0.001	0.087	-0.055	-0.051	0.04	-0.022*	0.067***	0.045**	-0.023	0.012
	(1.35)	(1.34)	(-2.48)	(-3.27)	(-0.07)	(1.29)	(-0.23)	(-0.69)	(0.38)	(-1.88)	(4.54)	(2.09)	(-0.91)	(0.60)
Adj.R^2	0.689	0.689												
N	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553

F	63.81	23.43												
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.7: How Does the Stock Market Value Managers' Influence?

This table shows results for the impact of the number of shared executives (#Shared Executives) between parent bank holding companies (BHCs) with their subsidiary banks and the valuation of the BHCs. We use the market-to-book ratio (MTB) to measure valuation. We use OLS analysis to examine the effect because our instrumental variable fails to meet the exclusion condition at the bank holding company level. The ordinary least square regression (OLS) analysis Column (1) shows the results of the OLS regression with BHC fixed effects. Column (2) shows the results of the OLS regression with Time fixed effects. Column (1) shows the results of the OLS regression with both BHC fixed effects and time fixed effects. The sample period is from 2007 to 2017. *, **, and *** denote significance at 10%, 5%, and 1% level.

	(1)	**(2)**	**(3)**
Dependent Variable:	**MTB**	**MTB**	**MTB**
#Shared Executives_BHC	0.010***	0.003**	0.004**
	(6.75)	(2.00)	(2.47)
log(GTA)	-0.000	0.001	0.000
	(-0.29)	(0.70)	(0.01)
Capital Ratio	0.027	0.016	0.023
	(1.12)	(0.36)	(1.04)
Adj. R^2	0.547	0.257	0.742
N	766	776	766
BHC FE	Yes		Yes
Time FE		Yes	Yes

References

Acharya, V. V., Almeida, H., Ippolito, F., & Perez, A. (2014). Credit lines as monitored liquidity insurance: Theory and evidence. *Journal of Financial Economics*, 112(3), 287-319.

Acharya, V. V., Engle III, R. F., & Steffen, S. (2021). Why did bank stocks crash during COVID-19? (No. w28559). National Bureau of Economic Research.

Acharya, V. V., & Steffen, S. (2020). The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. *The Review of Corporate Finance Studies*, 9(3), 430-471.

Acharya, V., & Yorulmazer, T. (2007). Too many to fail: An analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation*, 16, 1-31.

Acharya, V., & Yorulmazer, T. (2008). Information contagion and bank herding. *Journal of Money, Credit and Banking*, 40, 215-231.

Aebi, V., Sabato, G., & Schmid, M. (2012). Risk management, corporate governance, and bank performance in the financial crisis. *Journal of Banking and Finance*, 36(12), 3213-3226.

Agca, S., Babich, V., Birge, J., & Wu, J. (2021). Credit risk propagation along supply chains: Evidence from the CDS market. *Management Science*. https://doi.org/10.1287/mnsc.2021.4174

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly*, 45(3), 425–455.

Amati, V., Lomi, A., Mascia, D., & Pallotti, F. (2021). The co-evolution of organizational and network structure: The role of multilevel mixing and closure mechanisms. *Organizational Research Methods*, 24, 285-318.

Angelini, P., Di Salvo, R., & Ferri, G. (1998). Availability and cost of credit for small businesses: Customer relationships and credit cooperatives. *Journal of Banking and Finance*, 22, 925-954.

Antón, M., & Polk, C. (2014). Connected stocks. *The Journal of Finance*, 69, 1099-1127.

Armitage, S. (1995). Banks' information about borrowers: The stock market response to syndicated loan announcements in the UK. *Applied Financial Economics*, 5(6), 449-459.

Bailey, W., Huang, W., & Yang, Z. (2011). Bank loans with Chinese characteristics: Some evidence on inside debt in a state-controlled banking system. *The Journal of Financial and Quantitative Analysis*, 46(6), 1795-1830.

Barro, J. R., & Barro, R. J. (1990). Pay, performance, and turnover of bank CEOs. *Journal of Labor Economics*, 8, 448–481.

Belenzon, S., & Tsolmon, U. (2016). Market frictions and the competitive advantage of internal labor markets. *Strategic Management Journal*, 37, 1280-1303.

Bennedsen, M., Nielsen, K. M., Perez-Gonzalez, F., & Wolfenzon, D. (2007). Inside the family firm: The role of families in succession decisions and performance. *Quarterly Journal of Economics*, 122, 647-691.

Bennedsen, M., Perez-Gonzalez, F., & Wolfenzon, D. (2020). Do CEOs matter? Evidence from hospitalization events. *Journal of Finance*, 75, 1877–1911.

Benveniste, L. M., & Spindt, P. A. (1989). How investment bankers determine the offer price and allocation of new issues. *Journal of Financial Economics*, 24, 343-361.

Berlin, M., & Loeys, J. (1988). Bond covenants and delegated monitoring. *The Journal of Finance*, 432, 397-412.

Bharath, S., Dahiya, S., Saunders, A., & Srinivasan, A. (2007). So what do I get? The bank's view of lending relationships. *Journal of Financial Economics*, 85, 368-419.

Bharath, S., Dahiya, S., Saunders, A., & Srinivasan, A. (2011). Lending relationships and loan contract terms. *Review of Financial Studies*, 24, 1141-1203.

Berger, A. N., Imbierowicz, B., & Rauch, C. (2016). The roles of corporate governance in bank failures during the recent financial crisis. *Journal of Money, Credit and Banking*, 48, 729-770.

Berger, A. N., & Bouwman, C. H. S. (2009). Bank liquidity creation. *The Review of Financial Studies*, 22(9), 3779-3837.

Berger, A. N., & Bouwman, C. H. S. (2017). Bank liquidity creation, monetary policy, and financial crises. *Journal of Financial Stability*, 30, 139-155.

Berger, A. N., Bouwman, C. H. S., Kick, T., & Schaeck, K. (2016). Bank liquidity creation following regulatory interventions and capital support. *Journal of Financial Intermediation*, 26(C), 115-141.

Berger, A. N., Bouwman, C. H., Norden, L., Roman, R. A., Udell, G. F., & Wang, T. (2020). Is a friend in need a friend indeed? How relationship borrowers fare during the COVID-19 crisis. Working Paper.

Berger, A. N., Chen, R., El Ghoul, S., & Guedhami, O. (2020). Who wins and who loses from bank geographic deregulation? Analysis of financially constrained and unconstrained firms. *Journal of Corporate Finance*, Forthcoming.

Berger, A. N., Chronopoulos, D. K., Sobiech, A. L., & Wilson, J. O. S. (2023). Taxation and bank liquidity creation. Working paper.

Berger, A. N., Karakaplan, M. U., & Roman, R. A. (2023). Whose bailout is it anyway? Political connections of small businesses vs. banks in PPP bailouts. *Journal of Financial Intermediation*, 56.

Berger, A. N., Cai, J., Roman, R. A., & Sedunov, J. (2022). Supervisory enforcement actions against banks and systemic risk. *Journal of Banking and Finance*, 140, Article 106222.

Berger, A. N., & Sedunov, J. (2017). Bank liquidity creation and real economic output. *Journal of Banking Finance*, 81, 1–19. https://doi.org/10.1016/j.jbankfin.2017.04.005.

Berger, A. N., & Black, L. K. (2019). Small business lending: The roles of technology and regulation from pre-crisis to crisis to recovery. In *The Oxford Handbook of Banking* (pp. 431-469). Oxford: Oxford University Press.

Berger, A. N., & Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *The Journal of Business*, 68(3), 351-381.

Berger, A. N., Zhang, D., & Zhao, Y. (2020). Bank specialness, credit lines, and loan structure. SSRN Working Paper. http://dx.doi.org/10.2139/ssrn.3276666

Bertrand, M., & Schoar, A. (2003). Managing with style: The effect of managers on firm policies. *Quarterly Journal of Economics*, 118, 1169-1208.

Best, R., & Zhang, H. (1993). Alternative information sources and the information content of bank loans. *The Journal of Finance*, 48(4), 1507-1522.

Bidwell, M. (2011). Paying more to get less: The effects of external hiring versus internal mobility. *Administrative Science Quarterly*, 56, 369-407.

Bidwell, M., & Keller, J. R. (2014). Within or without? How firms combine internal and external labor markets to fill jobs. *The Academy of Management Journal*, 57, 1035-1055.

Billett, M. T., Flannery, M. J., & Garfinkel, J. A. (2006). Are bank loans special? Evidence on the post-announcement performance of bank borrowers. *The Journal of Financial and Quantitative Analysis*, 41(4), 733-751.

Bloom, N., Eifert, B., McKenzie, D., Mahajan, A., & Roberts, J. (2013). Does management matter? Evidence from India. *Quarterly Journal of Economics*, 128, 1–51.

Bolton, P., Freixas, X., Gambacorta, L., & Mistrulli, P. E. (2016). Relationship and transaction lending in a crisis. *Review of Financial Studies*, 29, 2643-2676.

Boot, A. W., & Thakor, A. V. (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review*, 35(4), 899-920.

Boot, A. W., & Thakor, A. V. (2000). Can relationship banking survive competition? *The Journal of Finance*, 55(2), 679-713.

Borri, N., & Di Giorgio, G. (2022). Systemic risk and the COVID challenge in the European banking sector. *Journal of Banking & Finance*, 140, p.106073.

Brous, P. A., & Leggett, K. (1996). Wealth effects of enforcement actions against financially distressed banks. *Journal of Financial Research*, 19(4), 561–577.

Brown, C. O., & Dinç, I. S. (2011). Too many to fail? Evidence of regulatory forbearance when the banking sector is weak. *The Review of Financial Studies*, 24(4), 1378–1405.

Bu, C., Rogers, J., & Wu, W. (2021). A unified measure of Fed monetary policy shocks. *Journal of Monetary Economics*, 118, 331-349. https://doi.org/10.1016/j.jmoneco.2020.11.002.

Burt, R. S., & Kenz, M. (1995). Kinds of third-party effects on trust. *Rationality and Society*, 7(3), 255–292.

Bryant, J. (1980). A model of reserves, bank runs, and deposit insurance. *Journal of Banking and Finance*, 4(4), 335-344.

Boubakri, N., Chen, R., El Ghoul, S., & Guedhami, O. (2020). State ownership and debt structure. Working Paper.

Boubakri, N., El Ghoul, S., Guedhami, O., & Megginson, W. (2018). The market value of government ownership. *Journal of Corporate Finance*, 50, 44-65.

Boyd, J. H., & Prescott, E. C. (1986). Financial intermediary-coalitions. *Journal of Economic Theory*, 38(2), 211-232.

Calomiris, C. W., & Pornrojnangkool, T. (2009). Relationship banking and the pricing of financial services. *Journal of Financial Services Research*, 35, 189-224.

Campbell, T. C., Gallmeyer, M., Johnson, S. A., Rutherford, J., & Stanley, B. W. (2011). CEO optimism and forced turnover. *Journal of Financial Economics*, 101, 695-712.

Carnahan, S., Kryscynski, D., & Olson, D. (2017). When does corporate social responsibility reduce employee turnover? Evidence from attorneys before and after 9/11. *Academy of Management Journal*, 60, 1932-1962.

Cen, L., Dasgupta, S., Elkamhi, R., & Pungaliya, R. S. (2016). Reputation and loan contract terms: The role of principal customers. *Review of Finance*, 20(2), 501–533.

Chauvin, J., & Poliquin, C. (2021). Worker redeployment in multi-business firms. Working paper.

Chemmanur, T. J., & Fulghieri, P. (1994). Reputation, renegotiation, and the choice between bank loans and publicly traded debt. *The Review of Financial Studies*, 7(3), 475-506.

Chakraborty, A., & Hu, C. X. (2006). Lending relationships in line-of-credit and nonline-of-credit loans: Evidence from collateral use in small business. *Journal of Financial Intermediation*, 15, 86-107.

Chava, S., & Roberts, M. R. (2008). How does financing impact investment? The role of debt covenants. *Journal of Finance*, 63, 2085-2121.

Chen, K., Chen, Z., & Wei, K. (2011). Agency costs of free cash flow and the effect of shareholder rights on the implied cost of equity capital. *The Journal of Financial and Quantitative Analysis*, 46(1), 171-207.

Chetty, R., Friedman, J., Hendren, N., Stepner, M. (2020). The economic impacts of COVID-19: Evidence from a new public database built from private sector data. Opportunity Insights. Working Paper.

Chodorow-Reich, G., Darmouni, O., Luck, S., Plosser, M. (2022). Bank liquidity provision across the firm size distribution. *Journal of Financial Economics*, 144, 908-932.

Chodorow-Reich, G. (2013). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics*, 129(1), 1–59.

Claessens, S., Djankov, S., Fan, J. P., & Lang, L. H. (2002). Disentangling the incentive and entrenchment effects of large shareholdings. *The Journal of Finance*, 57(6), 2741-2771.

Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American Journal of Sociology,* 100(5), 1261–1293.

Cohen, L., & Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance*, 63, 1977-2011.

Cole, R. A. (1998). The importance of relationships to the availability of credit. *Journal of Banking & Finance*, 22(6-8), 959-977.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95-S120.

Colla, P., Ippolito, F., & Li, K. (2013). Debt specialization. *The Journal of Finance*, 68(5), 2117-2141.

Colla, P., Ippolito, F., & Li, K. (2020). Debt structure. *Annual Review of Financial Economics*, 12, 193-215.

Compello, M., & Gao, J. (2017). Customer concentration and loan contract terms. *Journal of Financial Economics*, 123(1), 108-136.

Cranmer, S. J., Desmarais, B. A., & Menninga, E. J. (2012). Complex dependencies in the alliance network. *Conflict Management and Peace Science*, 29(3), 279–313.

Cziraki, P., & Groen-Xu, M. (2020). CEO turnover and volatility under long-term employment contracts. *Journal of Financial and Quantitative Analysis*, 55, 1757–1791.

Dass, N., & Massa, M. (2011). The impact of strong bank-firm relationship on the borrowing firm. *The Review of Financial Studies*, 24, 1204-1260.

Datta, S., Iskandar-Datta, M., & Patel, A. (1999). Bank monitoring and the pricing of corporate public debt. *Journal of Financial Economics,* 51(3), 435-449.

De Fiore, F., & Uhlig, H. (2011). Bank finance versus bond finance. *Journal of Money, Credit and Banking*, 43(7), 1399-1421.

Degryse, H., & Van Cayseele, P. (2000). Relationship lending within a bank-based system: Evidence from European small business data. *Journal of Financial Intermediation*, 9, 90-109.

Delis, M. D., Iosifidi, M., Kokas, S., Xefteris, D., & Ongena, S. (2020). Enforcement actions on banks and the structure of loan syndicates. *Journal of Corporate Finance*, 60(2020), 101527.

Delis, M. D., Staikouras, P. K., & Tsoumas, C. (2017). Formal enforcement actions and bank behavior. *Management Science*, 63(4), 959–87.

Delis, M. D., Staikouras, P. K., & Tsoumas, C. (2019). Supervisory enforcement actions and bank deposits. *Journal of Banking and Finance*, 106 (2019), 110-123.

Demirgüç-Kunt, A., & Levine, R. (1999). Bank-based and market-based financial systems: Cross-country comparisons. Working Paper. https://ssrn.com/abstract=569255

Denis, D. J., & Mihov, V. T. (2003). The choice among bank debt, non-bank private debt, and public debt: Evidence from new corporate borrowings. *Journal of Financial Economics*, 70(1), 3-28.

Dennis, S., & Mullineaux, D. (2000). Syndicated loans. *Journal of Financial Intermediation*, 9, 404-426.

Dhaliwal, D. S., Khurana, I. K., & Pereira, R. (2011). Firm disclosure policy and the choice between private and public debt. *Contemporary Accounting Research*, 28(1), 293-330.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3), 393-414.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3), 401-419.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy*, 99(n. 40), 689-721.

Drucker, S., & Puri, M. (2005). On the benefits of concurrent lending and underwriting. *Journal of Finance*, 60, 2763-2799.

Duan, Y., El Ghoul, S., Guedhami, O., Li, H., & Li, X. (2021). Bank systemic risk around COVID-19: A cross-country analysis. *Journal of Banking & Finance*, 133, p.106299.

Dyer, J., & Nobeoka, K. (2000). Creating and managing a high-performance knowledge-sharing network: The Toyota case. *Strategic Management Journal*, 21, 345-367.

Entwisle, B., Faust, K., Rindfuss, R. R., & Kaneda, T. (2007). Networks and contexts: Variation in the structure of social ties. *American Journal of Sociology*, 112(5), 1495-1533.

Elsas, R., & Krahnen, J. P. (1998). Is relationship lending special? Evidence from credit-file data in Germany. *Journal of Banking & Finance*, 22(10-11), 1283-1316.

Fama, E. F. (1985). What's different about banks? *Journal of Monetary Economics*, 15(1), 29-39.

Fafchamps, M., van der Leij, M. J., & Goyal, S. (2010). Matching and network effects. *Journal of the European Economic Association*, 8, 203-231.

Fields, L. P., Fraser, D. R., Berry, T. L., & Byers, S. (2006). Do bank loan relationships still matter? *Journal of Money, Credit and Banking*, 38(5), 1195-1209.

Fisman, R., Khurana, R., & Rhodes-Kropf, M. (2014). Governance and CEO turnover: Do something or do the right thing? *Management Science*, 60, 319–337.

Frank, M. Z., & Goyal, V. K. (2003). Testing the pecking order theory of capital structure. *Journal of Financial Economics*, 67(2), 217-248.

Gande, A., & Saunders, A. (2012). Are banks still special when there is a secondary market for loans? *The Journal of Finance*, 67(5), 1649-1684.

Giacomini, E., Kumar, N., & Naranjo, A. (2022). Inter-firm relationships and the special role of common banks. Working Paper.

Graham, J. R. (1996). Debt and the marginal tax rate. *Journal of Financial Economics*, 41(1), 41-73.

Graham, J. R., & Leary, M. T. (2011). A review of empirical capital structure research and directions for the future. *Annual Review of Financial Economics*, 3(1), 309-345.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6), 1360–1380.

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Journal of Sociology*, 91(3), 481–510. http://www.jstor.org/stable/2780199.

Greenwald, D., Krainer, J., & Paul, P. (2021). The credit line channel. Federal Reserve Bank of San Francisco Working Paper 2020-26.

Groysberg, B., Lee, L.-E., & Nanda, A. (2008). Can they take it with them? The portability of star knowledge workers' performance. *Management Science*, 54, 1213-1230.

Hackbarth, D., Hennessy, C. A., & Leland, H. E. (2007). Can the trade-off theory explain debt structure? *The Review of Financial Studies*, 20(5), 1389-1428.

Hadlock, C. J., & James, C. M. (2002). Do banks provide financial slack? *The Journal of Finance*, 57(3), 1383-1419.

Hale Jr., D., Ployhart, R. E., & Shepherd, W. (2016). A two-phase longitudinal model of a turnover event: Disruption, recovery rates, and moderators of collective performance. *Academy of Management Journal*, 59, 906-929.

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., Tatlow, H., (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nat Hum Behav.*, 5(4), 529-538. doi: 10.1038/s41562-021-01079-8.

Harford, J., Mansi, S. A., & Maxwell, W. F. (2008). Corporate governance and firm cash holdings in the US. *Journal of Financial Economics*, 87(3), 535-555.

Harhoff, D., & Körting, T. (1998). Lending relationships in Germany – Empirical evidence from survey data. *Journal of Banking and Finance,* 22, 1317-1353.

Hernández-Cánovas, G., & Martínez-Solano, P. (2010). Relationship lending and SME financing in the continental European bank-based system. *Small Business Economics*, 34, 465-482.

Herrera, A. M., & Minetti, R. (2007). Informed finance and technological change: Evidence from credit relationships. *Journal of Financial Economics*, 83(1), 223-269.

Holmström, B., & Tirole, J. (1998). Private and public supply of liquidity. *Journal of Political Economy*, 106(1), 1-40.

Houston, J., & James, C. (1996). Bank information monopolies and the mix of private and public debt claims. *The Journal of Finance,* 51(5), 1863-1889.

Hovakimian, A., Opler, T., & Titman, S. (2001). The debt-equity choice. *Journal of Financial and Quantitative Analysis*, 36(1), 1-24.

Huang, S., Maharjan, J., & Thakor, A. V. (2020). Disagreement-induced CEO turnover. *Journal of Financial Intermediation*, 43, 1-19.

Huneeus, C., Huneeus, F., Larrain, B., Larrain, M., & Prem, M. (2021). The internal labor markets of business groups. *Journal of Corporate Finance*, 69, 929-1199.

Huson, M. R., Parrino, R., & Starks, L. T. (2001). Internal monitoring mechanisms and CEO turnover: A long-term perspective. *Journal of Finance,* 56, 2265–2297.

Ivashina, V. (2009). Asymmetric information effects on loan spreads. *Journal of Financial Economics*, 90(2), 300-319.

Jackson, M. O., & Pernoud, A. (2021). Systemic risk in financial networks: A survey. *Annual Review of Economics*, 12(1),171-202.

Jackson, M. O., Rogers, B. W., & Zenou, Y. (2017). The economic consequences of social-network structure. *Journal of Economic Literature*, 55(1), 49–95.

James, C. (1987). Some evidence on the uniqueness of bank loans. *Journal of Finance Economics*, 19(2), 217-235.

Jiang, W. (2017). Have instrumental variables brought us closer to the truth. *Review of Corporate Finance Studies*, 6(2), 127-140.

Jimenez, G., Ongena, S., Peydro, J., & Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank-balance sheet channel with loan applications. *American Economic Review*, 102, 2121-2165.

John, K., Kaviani, M., Kryzanowski, L., & Maleki, H. (2018). Do country-level creditor protections affect firm-level debt structure? Fox School of Business Research Paper No.18-012.

Johnson, W. B., Magee, R. P., Nagarajan, N. J., & Newman, H. A. (1985). An analysis of the stock price reaction to sudden executive deaths: Implications for the managerial labor market. *Journal of Accounting and Economics*, 7, 151 – 174.

Johnson, S. A. (1997). An empirical analysis of the determinants of corporate debt ownership structure. *The Journal of Financial and Quantitative Analysis*, 32, 47-69.

Johnson, S. A. (1998). The effect of bank debt on optimal capital structure. *Financial Management*, 27, 47-56.

Kalcheva, I., & Lins, K. V. (2007). International evidence on cash holdings and expected managerial agency problems. *The Review of Financial Studies*, 20(4), 1087-1112.

Kapan, T., & Minoiu, C. (2021). Liquidity insurance vs. credit provision: Evidence from the COVID-19 crisis. *Credit Provision: Evidence from the COVID-19 Crisis* (September 30, 2021).

Kashyap, A. K., Rajan, R., & Stein, J. C. (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *The Journal of Finance*, 57(1), 33-73.

Klein, A. (1998). Firm performance and board committee structure. *The Journal of Law and Economics*, 41(1), 275-304.

Kleymenova, A., & Tomy, R. E. (2021). Observing enforcement: Evidence from banking. Chicago Booth Research Paper 19-05.

Kogut, B., & Walker, G. (2001). The small world of Germany and the durability of national networks. *American Sociological Review*, 66, 317-335.

Kysucky, V., & Norden, L. (2016). The benefits of relationship lending in a cross-country context: A meta-analysis. *Management Science*, 62(1), i-vii.

Leland, H. E. (1998). Agency costs, risk management, and capital structure. *The Journal of Finance*, 53(4), 1213-1243.

Li, C., & Ongena, S. (2015). Bank loan announcements and borrower stock returns before and during the recent financial crisis. *Journal of Financial Stability*, 21, 1-12.

Li, L., Strahan, P. E., & Zhang, S. (2020). Banks as lenders of first resort: Evidence from the COVID-19 crisis. *The Review of Corporate Finance Studies*, 9(3), 472-500.

Lins, K. V. (2003). Equity ownership and firm value in emerging markets. *The Journal of Financial and Quantitative Analysis*, 38(1), 159-184.

Lomi, A., & Pattison, P. (2006). Manufacturing relations: An empirical study of the organization of production across multiple networks. *Organization Science*, 17(3), 313-332.

López-Espinosa, G., Mayordomo, S., & Moreno, A. (2017). When does relationship lending start to pay? *Journal of Financial Intermediation*, 31, 16-29.

Lospinoso, J., & Snijders, T. A. (2019). Goodness of fit for stochastic actor-oriented models. *Methodological Innovations*, 12(3).

Lummer, S. L., & McConnell, J. J. (1989). Further evidence on the bank lending process and the capital-market response to bank loan agreements. *Journal of Financial Economics*, 25(1), 99-122.

Machauer, A., & Weber, M. (2000). Number of bank relationships: An indicator of competition, borrower quality, or just size? CFS Working Paper No. 2000/06.

Marsh, L. C., & Cormier, D. R. (2001). Spline regression models (No. 137). Newbury Park, CA: Sage.

Maskara, P. K., & Mullineaux, D. J. (2011). Information asymmetry and self-selection bias in bank loan announcement studies. *Journal of Financial Economics*, 101(3), 684-694.

McNeil, C., Niehaus, G., & Powers, E. (2004). Management turnover in subsidiaries of conglomerates versus stand-alone firms. *Journal of Financial Economics*, 72, 63-96.

Mikkelson, W. H., & Partch, M. M. (1986). Valuation effects of security offerings and the issuance process. *Journal of Financial Economics,* 15(1-2), 31-60.

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, 49(4), 261-297.

Morck, R., Shleifer, A., & Vishny, R. W. (1988). Management ownership and market valuation: An empirical analysis. *Journal of Financial Economics*, 20, 293-315.

Morck, R., Shleifer, A., & Vishny, R. W. (1989). Alternative mechanisms for corporate control. *American Economic Review*, 79, 842–852.

Myers, S., & Majluf, N. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13, 187-221.

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review*, 23, 242-266.

Opler, T. C., & Titman, S. (1994). Financial distress and corporate performance. *The Journal of Finance*, 49(3), 1015-1040.

Parsons, C., & Titman, S. (2009). Empirical capital structure: A review. Norwell, MA: Now Publishers Inc.

Pereira, J., Malafronte, I., Sorwar, G., & Nurullah, M. (2019). Enforcement actions, market movement and depositors' reaction: Evidence from the US banking system. *Journal of Financial Services Research*, 55(2), 143-165.

Perez-Gonzalez, F. (2006). Inherited control and firm performance. *American Economic Review*, 96, 1559–1588.

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance,* 49(1), 3-37.

Petersen, M. A., & Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics*, 110(2), 407-443.

Prilmeier, R. (2017). Why do loans contain covenants? Evidence from lending relationships. *Journal of Financial Economics,* 123(3), 558–579.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of Finance,* 47(4), 1367-1400.

Ramakrishnan, R. T., & Thakor, A. V. (1984). Information reliability and a theory of financial intermediation. *The Review of Economic Studies*, 51(3), 415-432.

Rapoport, A. (1953). Spread of information through a population with socio-structural bias: I. Assumption of transitivity. *Bulletin of Mathematical Biophysics*, 15, 523–533.

Roman, R. A. (2020). Winners and losers from supervisory enforcement actions against banks. *Journal of Corporate Finance*, 60 (2020) 101516.

Ross, D. G. (2010). The dominant bank effect: How high lender reputation affects the information content and terms of bank loans. *The Review of Financial Studies*, 23(7), 2730-2760.

Saheruddin, H. (2017). Are bank loans still special? Evidence during normal times and financial crises. Working Paper.

Schaeck, K., Cihak, M., Maechler, A., & Stolz, S. (2012). Who disciplines bank managers? *Review of Finance*, 16(1), 197–243.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, 80(3), 465–479. http://www.jstor.org/stable/2006678.

Schwert, M. (2018). Bank capital and lending relationships. *The Journal of Finance*, 73, 787-830. https://doi.org/10.1111/jofi.12604

Schilling, M., & Phelps, C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science*, 53, 1113-1126.

Sette, E., & Gobbi, G. (2015). Relationship lending during a financial crisis. *Journal of the European Economic Association*, 13, 453-481.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance,* 45(4), 1069-1087.

Srinivas, V., Byler, D., Wadhwani, R., Ranjan, A., & Krishna, V. (2015). Enforcement actions in the banking industry: Trends and lessons learned. Deloitte Centre for Financial Services, Deloitte University Press.

Slovin, M. B., Johnson, S. A., & Glascock, J. L. (1992). Firm size and the information content of bank loan announcements. *Journal of Banking & Finance,* 16(6), 1057-1071.

Snijders, T. A. B. (2001). The statistical evaluation of social network dynamics. *Sociological Methodology*, 31(1), 361–395.

Snijders, T. A. B., & Baervekdt, C. (2003). A multilevel network study of the effects of delinquent behavior on friendship evolution. *The Journal of Mathematical Sociology*, 27(2-3), 123-151.

Snijders, T. A. B. (2005). Models for longitudinal network data. *Models and Methods in Social Network Analysis*, 1, 215–247.

Snijders, T. A. B. (2017). Stochastic actor-oriented models for network dynamics. *Annual Review of Statistics and Its Application*, 4,343-363.

Snijders, T. A., Steglich, C., & Schweinberger, M. (2007). Modeling the coevolution of networks and behavior. In K. van Montfort, J. Oud, & A. Satorra (Eds.), *Longitudinal models in the behavioral and related sciences* (pp. 41–71). Lawrence Erlbaum Associates Publishers.

Steglich, C., Snijders, T. A., & Pearson, M. (2010). Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology*, 40(1), 329–393.

Sufi, A. (2007). Information asymmetry and financing arrangements: Evidence from syndicated loans. *Journal of Finance*, 62, 629-668.

Warner, J. B., Watts, R. L., & Wruck, K. H. (1988). Stock prices and top management changes. *Journal of Financial Economics*, 20, 461–492.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge University Press.

Weisbach, M. S. (1988). Outside directors and CEO turnover. *Journal of Financial Economics*, 20, 431-460.

Zhang, D., Zhang, Y., & Zhao, Y. (2022). Lending relationships and the pricing of syndicated loans. Working Paper. http://dx.doi.org/10.2139/ssrn.3519341.

Appendix A: Constructing Liquidity Creation Measure

Table A1: Liquidity classification of bank activities and construction of four liquidity creation measures

This table explains our methodology to construct liquidity creation measures in three steps.
Step 1: We classify all bank activities as liquid, semi-liquid, or illiquid. For activities other than loans, we combine information on product category and maturity. Due to data
limitations, we classify loans entirely by product category ("cat") or maturity ("mat").
Step 2: We assign weights to the activities classified in Step 1.

Assets

Illiquid assets (weight = ½)	**Semi-liquid assets (weight = 0)**	**Liquid assets (weight = - ½)**
Agricultural loans	Residential real estate loans	Cash and securities
Consumer loans All securities (regardless of maturity)	Consumer loans	Trading assets
Commercial and industrial loans	Loans to depository institutions	Federal funds sold
(C&I)	Loans to state and local governments	
Other loans and lease financing	Loans to foreign governments	

<u>Liabilities & Equity</u>		
Liquid liabilities (weight = ½)	**Semi-liquid liabilities (weight = 0)**	**Illiquid liabilities plus equity (weight = -½)**
Transactions deposits	Time deposits	Subordinated debt
Savings deposits	Other borrower money	Other liabilities
Federal funds purchased		Equity
Trading liabilities		

<u>OFF-BALANCE SHEET GUARANTEES (notional values):</u>

Illiquid guarantees (weight = ½)	**Semi-liquid guarantees & derivatives (weight = 0)**	**Liquid guarantees & derivatives (weight = - ½)**
Unused commitments	Net credit derivatives	Net participations acquired
Net standby letters of credit	Net securities lent	Interest rate derivatives
Commercial and similar letters of credit		Foreign exchange derivatives
All other off-balance sheet guarantees		Equity and commodity derivatives

Step 3: We combine bank activities as classified in Step 1 and as weighted in Step 2 to construct the liquidity creation.

LC_TOTAL=	+1/2*illiquid assets	+0*semi-liquid assets	-1/2*liquid assets
	+1/2*liquid liabilities	+0*semi-liquid liabilities	-1/2*illiquid liabilities
			-1/2*equity
			-1/2*liquid guarantees & derivatives

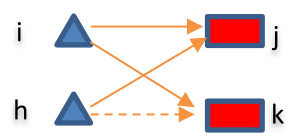
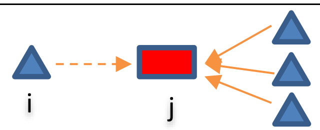
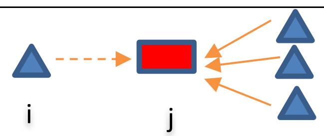
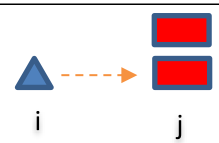
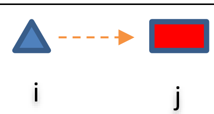
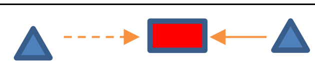
Appendix B: Network Terminology and Effects, and Robustness Checks

B1. Network Terminologies

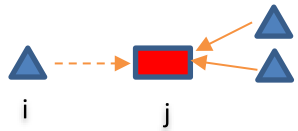
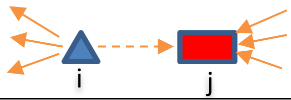
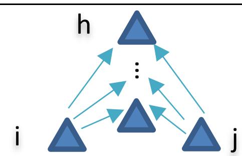
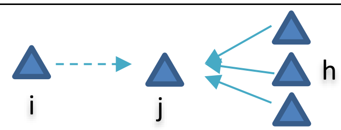
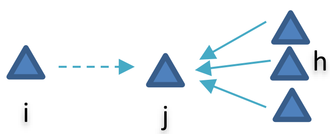
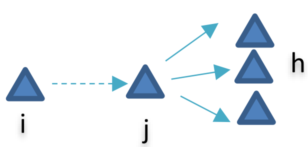
A social network consists of a finite set or sets of actors and the relation or relations defined on them (Faust and Wasserman, 1994). Actors are the decision-making and action-taking units in a network. They can be people, groups, and organizations. If a network consists of only one type of actors, then the network is a one-mode network. If a network consists of two types of actors, then the network is a two-mode network. Networks with more than two types of actors are possible but rare, and those networks are neither the focus of this paper nor social network analysis. Relation is a collection of specific kind of ties or relationships between among actors. Moreover, *Dyad*, is an essential concept related relationship. A dyad is a pair of actors and the (possible) relationship(s) between them. A dyad can consist with two actors with existing relationships or not-exist-but-possible relationships. Relationships and non-relationships, or more precisely, dyads, are the fundamental elements that compose a network. Moreover, a *triad* is a set of three actors and the dyads of them. In social network analysis, a triad is the smallest unit to measure network structures.

Table B1: Additional Effects in SAOMs

This table shows details about other effects in the estimation results of SAOMs in Table 2.3. Blue triangles represent firms. Red squares represent banks. Green lines represent banking relationships, blue lines represent supplying relationships. solid lines are preexisting relationships, and dash lines are new formed relationships. The coefficient, α, in GWESP, equals to log(2) by default.

Effect Name	Graphical Representation	Formula	Meaning of a positive coefficient
Banking Networks			
4-cycle		$\frac{1}{4}\sum_{i,j,h,k\ all\ different} l_{ij}l_{ik}l_{hj}l_{hk}$	Banks' customer portfolios are similar.
Indegree popularity		$\sum_j l_{ij}(\sum_{h\neq i} l_{hj}+1)$	Firms tend to have relationships with banks making a lot of loans
Indegree popularity, square root		$\sum_j l_{ij}\cdot\sqrt{(\sum_{h\neq i} l_{hj}+1)}$	Firms tend to have relationships with banks making a lot of loans. Adjusted for non-linearity.
Outdegree Truncated at 1		$\min(\sum_j l_{ij}, 1)$	Firms tend to have only one bank.
Anti in-isolates		$\sum_j I\{\sum_i l_{ij} \geq 1\}$	Banks tend to have at least one borrower.
Anti in-near-isolates		$\sum_j I\{\sum_i l_{ij} \geq 2\}$	Banks tend to have at least two borrowers.

i j

Indegree at least 3		$\sum_j I\{\sum_i l_{ij} \geq 3\}$	Banks tend to have at least three borrowers.
Out-in degree assortativity		$\sum_a l_{ij}\left(\sum_j l_{ij}\right)^{\frac{1}{2}}\left(\sum_i l_{ij}\right)^{\frac{1}{2}}$	Banks with a lot of firms tend to have relationships with firms with multiple banking relationships.
Supply chain networks			
Geometrically weighted edgewise shared partners, 2 out-stars		$\sum_{\substack{j=1;\\ j\neq i}}^{n} e^{\alpha}\{1-(1-e^{-\alpha})^{\sum_h s_{ih}s_{hj}}\}$	Firms tend to have overlapping customers.
Indegree popularity		$\sum_j s_{ij}(\sum_{h\neq i} s_{hj}+1)$	Firms tend to supply to customers with many suppliers.
Indegree popularity, square root		$\sum_j s_{ij}\cdot\sqrt{(\sum_{h\neq i} s_{hj}+1)}$	Firms tend to supply to customers with many suppliers. Adjusted for non-linearity.
Outdegree popularity		$\sum_j s_{ij}\sum_h s_{jh}$	Firms tend to supply to customers who have many customers.

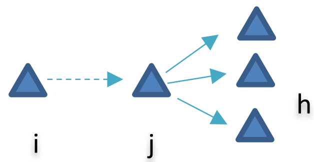
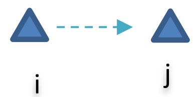
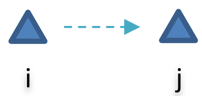
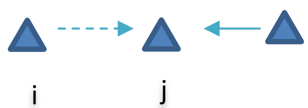
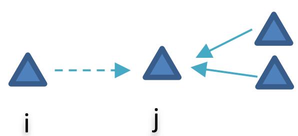
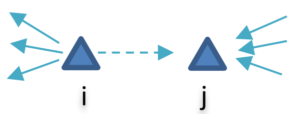
Outdegree popularity, square root		$\sum_j s_{ij}\sqrt{(\sum_h s_{jh})}$	Firms tend to supply to customers who have many customers. Adjusted for non-linearity.
Outdegree Truncated at 1		$\min\,(\sum_j s_{ij}\,, 1)$	Suppliers tend to have exclusive supply-chain relationships.
Anti in-isolates		$\sum_j I\{\sum_i s_{ij} \geq 1\}$	Firms tend to have at least one supplier.
Anti in-near-isolates		$\sum_j I\{\sum_i s_{ij} \geq 2\}$	Firms tend to have at least two suppliers.
Indegree at least 3		$\sum_j I\{\sum_i s_{ij} \geq 3\}$	Firms tend to have at least three suppliers.
Out-in degree assortativity		$\sum_j s_{ij}\left(\sum_j s_{ij}\right)^{\frac{1}{2}}\left(\sum_i s_{ij}\right)^{\frac{1}{2}}$	Suppliers supplying many customers tend to supply to customers with many suppliers.

Table B2: Measuring Closure Longer Time Horizon as A Robustness Check

This table presents the Ordinary least square analysis results for the implications of multilevel closure to bank loan terms. Columns (1)-(5) show the results for credit lines, and Columns (6)-(10) show the results for term loans. The dependent variables in both the left and right panels are loan spread (Spread), the natural log of loan amount (Amount), the natural log of loan maturity (Maturity), the number of financial covenants (#Covenant), and collateral requirement (Collateral), respectively. In Panel A, the main independent variables are ClosureLead5y and ClosureParti5y. ClosureLead5y is a dummy variable equals to one if the lead bank in a loan syndicate also lends to the supply chain partners of the borrower in the past five years, zero otherwise, and ClosureParti5y is a dummy variable equals to one if at least one participant banks in a loan syndicate also lend to the supply chain partners of the borrower in the past five years, zero otherwise. In Panel B, the main independent variables are ClosureLead5y and CountClosureParti5y. ClosureLead5y in this table is the same as the count of closure lead bank because each loan syndicate has only one lead bank. CountClosureParti5y is the number of participant banks in a loan syndicate that also lend to the supply chain partners of the borrower in the past five years. Variables in BankControls are BankSize, BankCapitalRatio, BankROA,TotalLoan, Liquidity, Efficiency, and MarketSensitivity. All regressions control for three-digit SIC industry fixed effects, lead bank fixed effects, and year fixed effects. t-statistics are reported in parentheses. The sample period is 2001-2020. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Lead Bank Closure V.S. Participant Bank Closure

	Credit Lines					**Term Loans**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Dependent Variables:	**Spread**	**Amount**	**Maturity**	**#Covenant**	**Collateral**	**Spread**	**Amount**	**Maturity**	**#Covenant**	**Collateral**
ClosureLead5y	14.331***	-0.141***	-0.073***	-0.012	0.036**	18.112***	-0.143**	0.012	-0.005	0.051*
	(5.14)	(-3.37)	(-3.46)	(-0.28)	(2.12)	(2.59)	(-2.28)	(0.41)	(-0.06)	(1.83)
ClosureParti5y	-17.567***	0.351***	0.126***	0.246***	-0.031*	-42.776***	0.345***	0.027	0.239***	-0.061**
	(-5.46)	(7.62)	(5.22)	(5.65)	(-1.91)	(-7.37)	(5.67)	(0.93)	(3.76)	(-2.43)
RelIntensity	-18.673***	0.189***	-0.070***	0.138***	-0.049***	-31.351***	0.148**	-0.060**	0.252***	-0.037
	(-7.40)	(6.03)	(-5.17)	(3.93)	(-3.47)	(-5.32)	(2.58)	(-2.35)	(4.07)	(-1.62)

BorrowerSize	-17.901***	0.482***	-0.051***	-0.223***	-0.105***	-10.706***	0.441***	-0.041***	-0.184***	-0.067***
	(-16.44)	(32.95)	(-7.30)	(-14.95)	(-17.26)	(-4.17)	(15.65)	(-4.05)	(-8.09)	(-6.97)
BorrowerROA	-343.409***	0.931***	0.448***	-0.225	-1.100***	-340.362***	0.499	0.794***	-0.080	-0.567***
	(-15.47)	(5.15)	(4.08)	(-0.92)	(-11.02)	(-8.12)	(1.26)	(4.53)	(-0.19)	(-3.82)
BorrowerBook Leverage	97.876***	0.537***	0.124*	0.060	0.397***	91.495***	0.328**	0.287***	-0.593***	0.332***
	(11.12)	(4.90)	(2.32)	(0.48)	(8.11)	(5.61)	(2.01)	(4.07)	(-3.41)	(5.09)
Borrower Tangibility	-7.684	-0.322***	-0.072	-0.084	-0.184***	31.168	-0.382*	-0.122	-0.061	-0.138
	(-0.58)	(-2.70)	(-1.18)	(-0.54)	(-3.05)	(1.15)	(-1.86)	(-1.30)	(-0.26)	(-1.58)
Borrower CashHolding	0.064	-0.991***	-0.086	-0.333	-0.109	43.747	-0.510	0.273*	-0.843**	-0.253
	(0.00)	(-5.59)	(-0.88)	(-1.37)	(-1.16)	(1.12)	(-1.39)	(1.95)	(-2.17)	(-1.61)
BankControls	14.331***	-0.141***	-0.073***	-0.012	0.036**	18.112***	-0.143**	0.012	-0.005	0.051*
IndustryFE	(5.14)	(-3.37)	(-3.46)	(-0.28)	(2.12)	(2.59)	(-2.28)	(0.41)	(-0.06)	(1.83)
BankFE	-17.567***	0.351***	0.126***	0.246***	-0.031*	-42.776***	0.345***	0.027	0.239***	-0.061**
YearFE	(-5.46)	(7.62)	(5.22)	(5.65)	(-1.91)	(-7.37)	(5.67)	(0.93)	(3.76)	(-2.43)
Constant	291.484***	16.623***	4.318***	3.002***	1.372***	332.881***	17.314***	4.286***	3.010***	1.222***
	(15.02)	(68.33)	(32.08)	(10.36)	(12.45)	(7.10)	(40.14)	(23.90)	(6.38)	(7.26)

Adj.R^2	0.542	0.701	0.308	0.237	0.372	0.437	0.643	0.220	0.351	0.284
N	7191	7191	7157	7191	7191	2916	2916	2890	2916	2916

Panel B: Intensive Margin

	Credit Lines					Term Loans				
Dependent Variables:	**(1) Spread**	**(2) Amount**	**(3) Maturity**	**(4) #Covenant**	**(5) Collateral**	**(6) Spread**	**(7) Amount**	**(8) Maturity**	**(9) #Covenant**	**(10) Collateral**
ClosureLead5y	5.348**	-0.031	-0.032**	-0.060**	0.010	13.213***	-0.018	0.026	-0.047	0.044***
	(1.99)	(-0.84)	(-2.22)	(-2.10)	(0.74)	(2.70)	(-0.42)	(1.30)	(-1.22)	(2.62)
CountClosureParti5y	-2.896***	0.060***	0.020***	0.055***	-0.002	-9.549***	0.070***	0.003	0.084***	-0.017***
	(-5.77)	(8.78)	(5.51)	(8.47)	(-0.78)	(-9.17)	(6.21)	(0.70)	(7.92)	(-3.09)
RelIntensity	-18.843***	0.191***	-0.069***	0.133***	-0.050***	-29.489***	0.147**	-0.056**	0.227***	-0.031
	(-7.38)	(6.21)	(-5.08)	(3.80)	(-3.56)	(-4.95)	(2.57)	(-2.20)	(3.72)	(-1.35)
BorrowerSize	-17.568***	0.472***	-0.053***	-0.233***	-0.105***	-10.903***	0.439***	-0.043***	-0.191***	-0.069***
	(-15.50)	(32.45)	(-7.50)	(-15.72)	(-17.06)	(-4.20)	(15.52)	(-4.11)	(-8.43)	(-7.09)
BorrowerROA	-345.150***	0.943***	0.456***	-0.252	-1.109***	-332.640***	0.468	0.802***	-0.196	-0.545***
	(-15.58)	(5.13)	(4.16)	(-1.04)	(-11.07)	(-8.07)	(1.17)	(4.60)	(-0.47)	(-3.75)
BorrowerBookLeverage	99.532***	0.510***	0.113**	0.047	0.401***	86.566***	0.337**	0.282***	-0.520***	0.319***
	(11.23)	(4.82)	(2.14)	(0.38)	(8.18)	(5.39)	(2.04)	(3.94)	(-3.00)	(4.92)
BorrowerTangibility	-5.616	-0.358***	-0.086	-0.099	-0.180***	26.278	-0.348*	-0.119	-0.008	-0.145*
	(-0.42)	(-3.05)	(-1.43)	(-0.62)	(-2.99)	(0.97)	(-1.69)	(-1.27)	(-0.03)	(-1.66)

BorrowerCashHolding	2.306	-1.036***	-0.104	-0.346	-0.104	41.655	-0.511	0.273*	-0.822**	-0.255
	(0.13)	(-5.91)	(-1.06)	(-1.44)	(-1.10)	(1.08)	(-1.40)	(1.95)	(-2.12)	(-1.64)
BankControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	287.097***	16.754***	4.361***	3.162***	1.371***	325.738***	17.351***	4.303***	3.124***	1.227***
	(14.83)	(69.35)	(32.64)	(10.98)	(12.46)	(7.06)	(40.72)	(24.07)	(6.73)	(7.33)
Adj.R^2	0.541	0.703	0.308	0.242	0.371	0.446	0.645	0.220	0.364	0.288
N	7191	7191	7157	7191	7191	2916	2916	2890	2916	2916

Appendix C: Bank Specialness Literature and Supplemental Tables for Chapter 3

C1. Brief Reviews of the Main Empirical Bank Specialness Literature Strands – Event Studies and Relationship Lending Papers

In this appendix A3, we briefly review two main empirical literature strands related to bank special specialness—event studies and relationship lending papers. These are not intended and should not be interpreted as complete literature reviews. Rather, our goals are to convey in a concise fashion that neither literature has reached consensus on whether and the extent and circumstances under which bank lending is special, and neither has attempted to confirm or refute the theoretical prediction that bank lending may be more special or only special when bank debt intensity is relatively high.

Turning first to the event studies, some find positive effects on corporate market returns of bank loan announcements (e.g., Mikkelson and Partch, 1986; James, 1987; Lummer and McConnell, 1989; Slovin, Johnson, and Glascock, 1992; Best and Zhang, 1993; Hadlock and James, 2002; Ross, 2010; Gande and Saunders, 2012). However, others find that bank specialness does not hold, or that the results vary by borrower type, loan type, time period, or which party made the announcement (e.g., Armitage, 1995; Billet, Flannery, and Garfinkel, 2006; Fields, Fraser, Berry, and Byers, 2006; Bailey, Huang, and Yang, 2011; Maskara and Mullineaux, 2011; Li and Ongena, 2015, Saheruddin, 2017). None to our knowledge examines whether the results differ when the corporations have very intense use of bank debt.

The number of empirical relationship lending papers is much larger and we review a smaller proportion of them. Most of the early studies examine the effects of banking relationships on interest rate spreads or other loan contract terms for small businesses. The majority find favorable effects for these businesses (e.g., Petersen and Rajan, 1994; Berger and Udell, 1995,Cole, 1998; Elsas and Krahnen, 1998; Harhoff and Körting, 1998; Machauer and Weber, 2000), while others find less favorable terms for these businesses (e.g., Angelini, Di Salvo, and Ferri, 1998; Degryse and Van Cayseele, 2000; Calomiris and Pornrojnangkool, 2009). Reviews by Kysucky and Norden (2016) and Berger and Black (2019) suggest that borrower benefits are more likely to occur—which we interpret here as evidence of bank loan specialness—when banking competition is more intense, which more often occurs in the U.S. than in other nations.

More of the later literature focuses on the effects of banking relationships on publicly traded corporations, which is the same type of firm studied in this paper. Most of these studies find benefits for the corporations as well as the banks, using a variety of different metrics (e.g., Dennis and Mullineaux, 2000; Drucker and Puri, 2005; Bharath, Dahiya, Saunders, and Srinivasan, 2007, 2011; Sufi, 2007). Neither the earlier literature on small businesses nor the later literature on corporations investigates differences by intensity of bank debt usage.

A third and even more recent empirical relationship lending literature focuses on how relationship borrowers fare relative to other borrowers during crises, as opposed to the normal times that typically dominate the other studies. It may be argued that benefits and costs to relationship borrowers or the role of bank specialness may be particularly important during crises when borrowers are generally most in need and the private information generated by banking relationships may be most valuable. Most studies of the effects of relationship lending during the GFC find that relationship borrowers fared well relative to other borrowers during this crisis, consistent with bank specialness during this critical time (e.g., Jimenez, Ongena, Peydro, and Saurina, 2012; Sette and Gobbi, 2015; Bolton, Freixas, Gambacorta and Mistrulli, 2016), although one study suggests some negative effects of relationships during the crisis (Chodorow-Reich, 2014).

Another study argues that the COVID-19 crisis may be more appropriate than the GFC and other crises for evaluating whether relationships help or hurt borrowers in need. This is because COVID-19 is exogenous and directly harms the borrowers, rather than the banks. Thus, the COVID-19 crisis directly causes the borrowers to be in need, rather than the GFC and other crises that more directly harm the banks, which may then reduce credit supply to their borrowers. This study finds strong evidence that relationship borrowers fare more poorly than other borrowers during the crisis, contrary to bank specialness, with some mitigation of these negative effects for smaller borrowers and smaller banks (Berger, Bouwman, Norden, Roman, Udell, and Wang, 2020). As above for studies focusing on normal times, none of the crisis studies examine how the effects differ by bank debt intensity.

Table C1: Summary Statistics of Debt Structure and Market-To-Book (MTB) Ratio by Country

This table presents the mean proportions for the seven types of debt and MTB ratio, as well as sample sizes in countries around the world.

Country Name	N	Term Loans	Credit Lines	Senior Bonds	Subordinated Bonds	Capital Leases	Commercial Paper	Other Debt	MTB
Argentina	723	60%	7%	24%	2%	3%	0%	5%	1.38
Australia	10,815	31%	31%	15%	1%	16%	0%	7%	1.77
Austria	965	55%	9%	18%	3%	4%	0%	9%	1.23
Bahamas	5	0%	100%	0%	0%	0%	0%	0%	1.10
Bahrain	199	53%	16%	18%	2%	0%	0%	11%	1.02
Bangladesh	1,344	61%	26%	1%	3%	4%	0%	5%	1.72
Belgium	1,524	54%	8%	14%	1%	10%	1%	13%	1.45
Belize	8	47%	12%	38%	0%	3%	0%	0%	1.56
Bermuda	4,478	63%	13%	14%	0%	5%	0%	6%	1.3
Botswana	90	50%	13%	15%	6%	10%	1%	6%	1.74
Brazil	2,935	53%	14%	18%	2%	1%	0%	11%	1.29

Bulgaria	403	47%	27%	8%	3%	11%	0%	4%	1.28
Burkina Faso	3	65%	35%	0%	0%	0%	0%	0%	2.28
Canada	12,663	30%	24%	27%	5%	7%	0%	5%	1.71
Cayman Islands	5618	62%	12%	17%	0%	3%	0%	6%	1.61
Chile	1,770	60%	1%	29%	1%	6%	0%	2%	1.26
China	23,554	82%	7%	7%	0%	2%	0%	2%	2.25
Colombia	408	47%	4%	23%	3%	6%	1%	16%	1.04
Cote d'Ivoire	91	56%	11%	6%	0%	0%	0%	27%	1.74
Croatia	769	83%	6%	2%	1%	2%	1%	6%	1.04
Curacao	28	75%	6%	14%	0%	0%	0%	6%	1.30
Cyprus	704	55%	29%	7%	1%	4%	0%	3%	0.81
Czech Rep.	112	51%	22%	12%	0%	10%	0%	5%	1.11
Denmark	1,840	64%	10%	11%	4%	6%	0%	4%	1.60
Ecuador	11	92%	2%	1%	0%	0%	4%	1%	2.17

Egypt	1,036	46%	33%	15%	0%	3%	0%	2%	1.28
Estonia	174	64%	13%	3%	0%	18%	0%	2%	1.39
Eswatini	2	49%	27%	22%	0%	1%	0%	0%	1.92
Faroe Islands	33	48%	27%	16%	10%	0%	0%	0%	1.27
Finland	1,823	65%	5%	14%	0%	7%	5%	4%	1.50
France	8,716	49%	14%	15%	1%	7%	1%	14%	1.46
Gabon	17	41%	31%	0%	0%	0%	0%	27%	1.56
Georgia	2	95%	0%	1%	3%	0%	0%	2%	1.07
Germany	7,656	62%	9%	14%	1%	7%	0%	7%	1.44
Ghana	107	51%	35%	5%	0%	4%	0%	3%	1.34
Greece	2,588	57%	7%	27%	1%	5%	0%	3%	1.09
Hong Kong	2,206	63%	11%	13%	2%	3%	0%	6%	1.13
Hungary	249	59%	15%	7%	2%	11%	0%	7%	1.34
Iceland	140	72%	8%	11%	2%	1%	0%	6%	1.33
India	24,628	45%	28%	4%	0%	1%	1%	21%	1.42
Indonesia	4,133	43%	34%	13%	1%	6%	0%	4%	1.46

Ireland	617	46%	18%	17%	1%	10%	0%	8%	1.47
Isle of Man	104	60%	19%	14%	0%	4%	0%	3%	1.32
Israel	2,829	59%	9%	26%	2%	2%	0%	2%	1.33
Italy	3,400	60%	12%	12%	1%	5%	0%	10%	1.32
Jamaica	219	54%	8%	5%	3%	5%	1%	25%	1.36
Japan	36,311	75%	6%	9%	0%	8%	0%	2%	1.16
Jordan	853	48%	38%	7%	0%	2%	0%	4%	1.15
Kazakhstan	105	32%	10%	29%	10%	3%	0%	16%	1.18
Kenya	347	57%	24%	8%	2%	1%	2%	5%	1.43
Korea	10,650	35%	35%	19%	0%	1%	1%	9%	1.23
Kuwait	998	71%	15%	5%	0%	3%	0%	4%	1.18
Latvia	265	51%	37%	1%	0%	10%	0%	2%	0.84
Lebanon	71	59%	16%	6%	18%	0%	0%	1%	1.02
Liberia	12	41%	4%	52%	0%	2%	0%	0%	1.08
Liechtenstein	29	35%	0%	65%	0%	0%	0%	0%	1.01
Lithuania	367	67%	12%	3%	0%	12%	0%	7%	1.16

Luxembourg	388	41%	21%	23%	2%	6%	1%	6%	1.28
Malawi	32	71%	19%	2%	1%	0%	5%	2%	2.76
Malaysia	11,262	42%	36%	7%	1%	8%	1%	6%	1.12
Malta	150	56%	9%	23%	9%	1%	0%	2%	1.89
Marshall Islands	27	81%	17%	1%	0%	0%	0%	0%	0.78
Mauritius	285	59%	21%	7%	2%	8%	0%	3%	1.10
Mexico	1,267	44%	8%	35%	1%	4%	0%	8%	1.33
Monaco	25	21%	38%	0%	0%	3%	0%	38%	1.18
Morocco	622	39%	21%	14%	1%	2%	0%	23%	1.56
Namibia	59	56%	14%	12%	7%	6%	0%	6%	1.32
Netherlands	1,760	43%	23%	18%	2%	6%	1%	7%	1.52
New Zealand	1,224	35%	37%	11%	1%	5%	2%	10%	1.61
Nigeria	913	46%	33%	9%	1%	4%	4%	4%	1.49
Norway	2,177	44%	13%	29%	1%	6%	0%	6%	1.35
Oman	747	76%	16%	2%	1%	2%	0%	3%	1.23

Pakistan	3,181	50%	32%	5%	0%	6%	0%	7%	1.25
Panama	41	44%	10%	25%	5%	10%	0%	6%	1.12
Papua New Guinea	56	74%	14%	4%	0%	7%	0%	0%	1.56
Peru	839	47%	13%	17%	2%	15%	0%	6%	1.04
Philippines	1,707	60%	13%	10%	2%	4%	0%	10%	1.51
Poland	4,862	29%	34%	11%	0%	16%	0%	9%	1.45
Portugal	696	50%	9%	20%	1%	5%	12%	4%	1.15
Qatar	315	67%	13%	8%	2%	3%	0%	7%	1.39
Romania	359	54%	29%	2%	0%	8%	1%	7%	0.96
Russian Federation	990	58%	11%	16%	1%	4%	0%	10%	1.25
Saudi Arabia	819	65%	23%	4%	2%	2%	0%	3%	1.73
Senegal	14	96%	4%	0%	0%	0%	0%	0%	2.07
Serbia	75	80%	4%	0%	0%	6%	0%	11%	0.98
Singapore	7,019	61%	19%	6%	0%	10%	0%	4%	1.22

Slovak Rep.	124	55%	13%	23%	2%	4%	0%	3%	1.00
Slovenia	309	81%	3%	6%	1%	1%	0%	7%	0.98
South Africa	3,169	40%	22%	10%	2%	10%	0%	15%	1.44
Spain	1,786	63%	11%	11%	1%	3%	0%	11%	1.52
Sri Lanka	2,354	52%	27%	3%	1%	5%	1%	11%	1.22
Sudan	10	50%	1%	0%	0%	49%	0%	0%	0.69
Sweden	4,366	54%	20%	12%	1%	7%	1%	5%	1.84
Switzerland	2,793	43%	12%	28%	1%	5%	1%	9%	1.54
Tanzania	47	71%	23%	3%	0%	2%	0%	1%	1.91
Thailand	6,141	56%	14%	14%	1%	10%	0%	5%	1.46
Togo	4	78%	9%	10%	1%	0%	0%	3%	1.05
Trinidad and Tobago	140	30%	18%	34%	0%	4%	0%	15%	1.50
Tunisia	481	56%	23%	9%	0%	3%	1%	8%	1.42
Turkey	3,086	80%	4%	3%	0%	5%	0%	7%	1.31
Uganda	29	85%	4%	0%	5%	0%	0%	6%	1.02

Ukraine	138	65%	4%	18%	5%	3%	0%	5%	1.27
United Arab Emirates	644	57%	22%	12%	1%	4%	0%	4%	1.10
United Kingdom	12,785	43%	26%	16%	1%	10%	0%	4%	1.58
United States	54,691	31%	17%	33%	5%	6%	1%	8%	1.87
Venezuela	116	59%	8%	15%	2%	1%	2%	13%	0.93
Vietnam	1,243	61%	31%	6%	0%	1%	0%	2%	1.12
West Bank and Gaza	102	70%	24%	6%	0%	0%	0%	1%	1.18
Zambia	105	59%	34%	2%	0%	3%	0%	1%	1.41
Zimbabwe	284	47%	36%	3%	0%	4%	0%	9%	1.53

Table C2: Summary Statistics of Debt Structure and Market-To-Book Ratio (MTB) by Year

This table presents the number of observations, the mean proportions for the seven types of debt and MTB ratio, as well as the sample size over time.

Year	N	Credit Lines	Term Loans	Senior Bonds	Subordinated Bonds	Capital Leases	Commercial Paper	Other Debts	MTB
2002	9,572	15.31%	45.70%	19.30%	3.31%	5.28%	0.65%	10.46%	1.26
2003	12,241	15.91%	45.17%	19.62%	3.28%	5.83%	0.59%	9.60%	1.58
2004	13,075	16.13%	45.64%	20.03%	2.79%	6.10%	0.59%	8.72%	1.63
2005	13,917	16.19%	47.45%	19.32%	2.57%	6.22%	0.61%	7.64%	1.64
2006	16,919	16.58%	51.82%	16.85%	1.90%	5.69%	0.60%	6.56%	1.63
2007	17,606	17.25%	51.71%	15.94%	1.69%	5.71%	0.58%	7.12%	1.68
2008	18,874	18.69%	51.85%	14.26%	1.52%	5.78%	0.46%	7.43%	1.17
2009	19,656	17.46%	52.75%	14.45%	1.51%	6.55%	0.41%	6.88%	1.42
2010	19,670	17.43%	52.76%	14.80%	1.49%	6.44%	0.36%	6.72%	1.49

2011	20,275	18.36%	52.66%	14.49%	1.33%	6.17%	0.39%	6.60%	1.33
2012	21,165	18.90%	52.25%	14.65%	1.18%	5.92%	0.37%	6.73%	1.36
2013	21,826	19.08%	51.73%	15.20%	1.21%	5.61%	0.38%	6.79%	1.50
2014	22,345	19.74%	50.81%	15.54%	1.20%	5.62%	0.44%	6.66%	1.58
2015	22,633	19.54%	51.14%	15.40%	1.12%	5.64%	0.47%	6.68%	1.70
2016	22,986	19.14%	51.33%	15.65%	1.14%	5.68%	0.54%	6.52%	1.70
2017	22,669	18.79%	51.75%	15.38%	0.99%	5.91%	0.45%	6.72%	1.73
2018	22,546	18.39%	52.30%	15.09%	0.97%	6.24%	0.47%	6.54%	1.53

Appendix D: Supplemental Tables for Chapter 4

Table D1: Do Characteristics of Managers Influence Firm Performance? -Additional Instrumental Variable Analysis

This table shows the results of the ordinary least square regressions of the effects of additional characteristics of the shared executives. Panel A displays the effect of the average tenure of the shared executives. Panel B displays the effect of the average age of the shared executives. Panel C displays the gender effect measured by the ratio of female executives in the shared executives. Panel D displays the effect of power, measured by the presence of CEOs in the shared executives. Panel E displays the effect of incentives, measured by the average total compensation of the shared executives. Columns (1) and (2) show the results for the two first-stage regressions. Columns (3)- (14) show the second stage results. We measure profitability using ROA in Column (3), ROE in Column (4), and net interest margin (NIM) in Column (5). Columns (6) to (9) show the results for the output quantity channel. We measure Output using commercial and industrial loans in Column (6), commercial and real estate loans (CRE) in Column (7), deposits in Column (8) and unused loan commitments (commitments) in Column (9). Columns (10) to (12) show the results for the cost efficiency channel. We measure costs using interest expenses in Column (10), non-interest expenses in Column (11), and total expenses in Column (12). Columns (13) and (14) show the result of the asset turnover channel with interest income and non-performing loans (NPL) as the dependent variables, respectively. In Panel B, Columns (1) and (2) show the results for the two first-stage regressions. Columns (6) – (14) are scaled by gross total assets (GTA). The sample period is from 2007 to 2017. *, **, and *** denote significance at 10%, 5%, and 1% level.

Panel A: Tenure

	First Stage			Profitability		Output Quantity		Cost Efficiency			Asset Turnover		Output Quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent Variable:	#Shared Executives	#Shared Executives *Avg. Tenure	ROA	ROE	NIM	C&I Loans/ GTA	CRE/ GTA	Deposits/GTA	Commitments/ GTA	Interest Expenses/ GTA	Non-Interest Expenses/ GTA	Total Expenses/ GTA	Interest Income/ GTA	NPL/ GTA

EA	-0.074*** (-3.40)	-0.194** (-2.16)												
EA* Avg. Tenure	-0.052 (-1.61)	-0.474*** (-3.19)												
#$\widehat{\text{Shared}}$ Executives* Avg. Tenure			-0.003 (-1.47)	-0.031 (-1.56)	-0.005*** (-2.62)	-0.002 (-0.57)	0.004 (0.27)	0.010 (0.96)	0.008 (0.52)	-0.002*** (-2.61)	-0.001 (-0.37)	-0.007*** (-2.71)	0.004 (1.28)	-0.003 (-1.47)
#$\widehat{\text{Shared}}$ Executives			0.022* (1.75)	0.245* (1.81)	0.041*** (2.91)	0.027 (0.93)	-0.052 (-0.54)	-0.061 (-1.32)	-0.090 (-1.04)	0.013*** (2.75)	0.006 (0.53)	0.053*** (2.97)	-0.036* (-1.74)	0.022* (1.75)
Avg. Tenure	0.327*** (9.64)	2.718*** (15.04)	0.000 (0.08)	0.005 (0.18)	0.002 (0.73)	-0.006* (-1.84)	0.008 (0.53)	-0.005 (-0.30)	0.011 (0.65)	0.001 (1.04)	0.000 (0.22)	0.003 (0.84)	0.001 (0.21)	0.000 (0.08)
log(GTA)	0.215 (1.53)	0.041 (0.08)	-0.010** (-2.40)	-0.105** (-2.33)	-0.004 (-0.69)	0.031*** (2.78)	0.018 (0.65)	-0.005 (-0.35)	0.032 (1.34)	-0.002 (-0.92)	0.002 (0.71)	-0.005 (-0.72)	0.014** (2.04)	-0.010** (-2.40)
Capital Ratio	1.076	-1.361	-0.083**	-0.950***	-0.033	0.071	-0.025	0.007	0.090	-0.033**	0.063***	-0.066	0.036	-0.083**

	(1.29)	(-0.47)	(-2.52)	(-3.04)	(-1.07)	(0.93)	(-0.09)	(0.08)	(0.56)	(-2.12)	(2.92)	(-1.49)	(1.01)	(-2.52)
N	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553
F	6.65	8.62												
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Age

	First Stage		Profitability			Output Quantity		Cost Efficiency		Asset Turnover			Output Quality	
Dependent Variable:	**(1) #Shared Executives**	**(2) #Shared Executives *Avg. Age**	**(3) ROA**	**(4) ROE**	**(5) NIM**	**(6) C&I Loans / GTA**	**(7) CRE/ GTA**	**(8) Deposits/GTA**	**(9) Commitments/ GTA**	**(10) Interest Expenses/ GTA**	**(11) Non-Interest Expenses/ GTA**	**(12) Total Expenses/ GTA**	**(13) Interest Income/ GTA**	**(14) NPL/ GTA**
EA	-0.082***	-3.032***												
	(-4.12)	(-3.30)												
EA* Avg. Age	-0.003	-0.135												
	(-1.16)	(-0.97)												
#$\widehat{\text{Shared}}$ Executives* Avg. Age			-0.001	-0.016	-0.003	-0.001	0.007	0.000	0.002	-0.001	-0.001	-0.004	0.002	-0.001
			(-0.87)	(-0.86)	(-0.80)	(-0.44)	(0.55)	(0.10)	(0.37)	(-0.84)	(-0.47)	(-0.81)	(0.84)	(-0.87)
#$\widehat{\text{Shared}}$ Executives			0.065	0.747	0.127	0.059	-0.308	-0.037	-0.138	0.042	0.033	0.166	-0.098	0.065
			(0.95)	(0.94)	(0.92)	(0.50)	(-0.58)	(-0.21)	(-0.53)	(0.94)	(0.51)	(0.92)	(-0.96)	(0.95)
Avg. Age	0.038***	2.510***	0.001	0.013	0.002	0.001	-0.006	0.000	-0.000	0.001	0.001	0.003	-0.001	0.001
	(13.11)	(16.02)	(0.72)	(0.71)	(0.64)	(0.23)	(-0.48)	(0.08)	(-0.05)	(0.68)	(0.43)	(0.65)	(-0.62)	(0.72)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
log(GTA)	0.078	0.573	-0.010	-0.104	-0.004	0.033***	0.027	-0.016	0.022	-0.002	0.001	-0.005	0.013	-0.010
	(0.63)	(0.09)	(-1.55)	(-1.41)	(-0.35)	(2.88)	(0.58)	(-1.13)	(1.11)	(-0.49)	(0.22)	(-0.36)	(1.40)	(-1.55)
Capital Ratio	-0.109	-31.842	-0.094*	-1.090*	-0.059	0.073	0.105	-0.065	0.041	-0.042	0.049	-0.100	0.046	-0.094*
	(-0.14)	(-0.88)	(-1.74)	(-1.80)	(-0.60)	(0.70)	(0.24)	(-0.46)	(0.21)	(-1.23)	(1.04)	(-0.76)	(0.68)	(-1.74)
N	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553
F	9.90	6.41												
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Gender

	First Stage		**Profitability**			**Output Quantity**				**Cost Efficiency**			**Asset Turnover**	**Output Quality**
Dependent Variable:	**(1) #Shared Executives**	**(2) #Shared Executives *Female%**	**(3) ROA**	**(4) ROE**	**(5) NIM**	**(6) C&I Loans/GTA**	**(7) CRE/GTA**	**(8) Deposits/GTA**	**(9) Commitments/GTA**	**(10) Interest Expenses/GTA**	**(11) Non-Interest Expenses/GTA**	**(12) Total Expenses/GTA**	**(13) Interest Income/GTA**	**(14) NPL/GTA**
EA	-0.173***	-0.003*												

	(-6.38)	(-1.75)												
EA* Female %	1.301***	0.153												
	(2.76)	(1.09)												
#$\widehat{\text{Shared}}$ Executives* Female %			0.375	3.914	-0.149	-0.424	-1.579	0.733	-0.134	-0.053	-0.100	-0.202	-0.180	0.375
			(0.96)	(0.96)	(-1.15)	(-1.06)	(-1.04)	(1.01)	(-0.48)	(-1.13)	(-1.03)	(-1.14)	(-0.84)	(0.96)
#$\widehat{\text{Shared}}$ Executives			-0.000	0.002	0.013***	0.010	0.010	-0.020	-0.025	0.004***	0.004	0.017***	-0.009	-0.000
			(-0.01)	(0.03)	(3.40)	(0.99)	(0.28)	(-1.16)	(-1.26)	(2.78)	(1.28)	(3.28)	(-1.44)	(-0.01)
Female %	3.246***	2.818***	-1.054	-11.000	0.381	1.140	4.392	-2.013	0.467	0.134	0.272	0.518	0.536	-1.054
	(4.19)	(9.91)	(-0.89)	(-0.89)	(0.98)	(0.94)	(0.96)	(-0.92)	(0.57)	(0.96)	(0.93)	(0.97)	(0.83)	(-0.89)
log(GTA)	0.217	0.010	-0.009	-0.094	0.003	0.039***	0.021	-0.021	0.020*	0.001	0.003*	0.004	0.010**	-0.009
	(1.37)	(0.78)	(-1.53)	(-1.48)	(1.09)	(3.54)	(0.85)	(-1.49)	(1.94)	(0.59)	(1.81)	(1.07)	(2.34)	(-1.53)
Capital Ratio	2.063	-0.037	-0.041	-0.506	-0.014	0.056	-0.160	0.000	0.038	-0.027**	0.060***	-0.040	0.003	-0.041
	(1.42)	(-0.52)	(-0.97)	(-1.20)	(-0.67)	(0.68)	(-0.57)	(0.00)	(0.34)	(-2.01)	(3.46)	(-1.25)	(0.09)	(-0.97)
N	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553
F	21.08	1.86												
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Power

	First Stage		**Profitability**			**Output Quantity**				**Cost Efficiency**			**Asset Turnover**	**Output Quality**
Dependent Variable:	**(1) #Shared Executives**	**(2) #Shared Executives *CEO**	**(3) ROA**	**(4) ROE**	**(5) NIM**	**(6) C&I Loans/ GTA**	**(7) CRE/ GTA**	**(8) Deposits/ GTA**	**(9) Commitments/GTA**	**(10) Interest Expenses/ GTA**	**(11) Non-Interest Expenses/ GTA**	**(12) Total Expenses/ GTA**	**(13) Interest Income/ GTA**	**(14) NPL/ GTA**
EA	-0.097***	-0.039***												
	(-4.36)	(-3.29)												
EA*CEO	-0.610***	-0.736***												
	(-2.66)	(-3.13)												
$\widehat{\#Shared}$ Executives*			-0.019*	-0.202*	-0.026**	0.002	0.003	0.060	0.060	-0.009**	0.001	-0.034**	0.029*	-0.019*

CEO			(-1.75)	(-1.77)	(-2.27)	(0.08)	(0.03)	(1.53)	(0.99)	(-2.24)	(0.14)	(-2.29)	(1.72)	(-1.75)
#$\widehat{\text{Shared}}$ Executives			0.018*	0.191*	0.029**	0.008	-0.017	-0.044	-0.077	0.010**	0.003	0.038**	-0.032*	0.018*
			(1.73)	(1.80)	(2.49)	(0.39)	(-0.24)	(-1.29)	(-1.35)	(2.24)	(0.33)	(2.45)	(-1.87)	(1.73)
CEO	2.010***	3.063***	0.001	0.013	0.002	0.001	-0.006	0.000	-0.000	0.001	0.001	0.003	-0.001	0.001
	(12.40)	(21.92)	(0.72)	(0.71)	(0.64)	(0.23)	(-0.48)	(0.08)	(-0.05)	(0.68)	(0.43)	(0.65)	(-0.62)	(0.72)
log(GTA)	0.282**	0.026	-0.010	-0.104	-0.004	0.033***	0.027	-0.016	0.022	-0.002	0.001	-0.005	0.013	-0.010
	(2.02)	(0.30)	(-1.55)	(-1.41)	(-0.35)	(2.88)	(0.58)	(-1.13)	(1.11)	(-0.49)	(0.22)	(-0.36)	(1.40)	(-1.55)
Capital Ratio	1.406	0.013	-0.094*	-1.090*	-0.059	0.073	0.105	-0.065	0.041	-0.042	0.049	-0.100	0.046	-0.094*
	(1.47)	(0.02)	(-1.74)	(-1.80)	(-0.60)	(0.70)	(0.24)	(-0.46)	(0.21)	(-1.23)	(1.04)	(-0.76)	(0.68)	(-1.74)
N	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553
F	13.39	10.64												
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel E: Incentives

	First Stage		Profitability			Output Quantity		Cost Efficiency		Asset Turnover			Output Quality	
Dependent Variable:	**(1) #Shared Executives**	**(2) #Shared Executives *Comp**	**(3) ROA**	**(4) ROE**	**(5) NIM**	**(6) C&I Loans / GTA**	**(7) CRE/ GTA**	**(8) Deposits/GTA**	**(9) Commitments/ GTA**	**(10) Interest Expenses/ GTA**	**(11) Non-Interest Expenses/ GTA**	**(12) Total Expenses/ GTA**	**(13) Interest Income/ GTA**	**(14) NPL/ GTA**
EA	-0.142***	-71.927**												
	(-5.28)	(-2.00)												
EA*Comp	-0.000***	-0.376***												
	(-4.45)	(-7.60)												
#$\widehat{\text{Shared}}$ Executives* Comp			-0.000	-0.000	-0.000***	0.000	-0.000	0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000
			(-1.53)	(-1.56)	(-2.84)	(0.98)	(-0.21)	(3.19)	(1.15)	(-2.91)	(0.12)	(-2.90)	(1.27)	(-1.53)
#$\widehat{\text{Shared}}$ Executives			0.008*	0.086**	0.016***	0.001	-0.020	-0.030**	-0.039	0.005***	0.003	0.020***	-0.015**	0.008*
			(1.96)	(2.07)	(3.23)	(0.14)	(-0.61)	(-2.08)	(-1.43)	(2.66)	(0.67)	(3.13)	(-2.18)	(1.96)

Comp	0.000***	2.147***	0.000	0.000	0.000***	-0.000***	0.000**	-0.000***	-0.000	0.000***	-0.000	0.000***	-0.000	0.000
	(4.35)	(7.67)	(1.35)	(1.18)	(3.60)	(-3.87)	(2.52)	(-3.46)	(-0.54)	(4.47)	(-1.14)	(3.83)	(-0.18)	(1.35)
log(GTA)	0.232	24.357	-0.007***	-0.074***	0.001	0.036***	0.012	-0.012	0.022*	-0.000	0.003*	0.001	0.009***	-0.007***
	(1.46)	(0.16)	(-3.24)	(-3.17)	(0.40)	(3.90)	(0.67)	(-1.22)	(1.86)	(-0.16)	(1.90)	(0.36)	(2.78)	(-3.24)
Capital Ratio	1.649	85.542	-0.069**	-0.788***	-0.007	0.091	-0.054	-0.027	0.053	-0.024*	0.067***	-0.031	0.016	-0.069**
	(1.30)	(0.07)	(-2.56)	(-3.38)	(-0.34)	(1.37)	(-0.22)	(-0.35)	(0.47)	(-1.89)	(4.34)	(-1.02)	(0.70)	(-2.56)
N	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553
F	21.74	37.14												
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes