Cohort phenomenon and increasing credit and liquidity risks of banks

Jairaj Gupta[a], Basim Alzugaiby[b], Anup Srivastava[c]*

[a] *Department of Finance, University of Birmingham*
Birmingham, B15 2TY, UK

[b] *College of Economics and Administrative Sciences, Al Imam Mohammad Ibn Saud Islamic University Riyadh, PO Box 5701, Saudi Arabia*

[c] *Haskayne School of Business, University of Calgary*
Calgary, Alberta T2N 1N4, Canada

December 2020

Abstract

We find that the average credit and liquidity risks of U.S. banks, the two principal determinants of bank distress, increased significantly over the last forty years or so. This trend stemmed from progressively aggressive business strategies adopted by new banking cohorts as well as old cohorts' shifts toward riskier business models. Each new cohort relied to a greater extent than its predecessor on brokered deposits, commercial real estate loans, off–balance sheet items, and noninterest income, factors that are associated with greater credit and liquidity risks. Importantly, the risk differences between the successive cohorts persist, indicating that newer cohorts use more and more aggressive business strategies as permanent business models, not just as entrance strategies. Older cohorts respond to changing markets by increasing aggressiveness of their own business models, which, in combination with the riskier business models of newcomers, increases the overall bank risks. Surprisingly, larger banks among old cohorts change their strategies faster than smaller banks from the same cohorts. These developments do not portend well for the stability of the banking sector as banks with riskier business models are more likely to fail in times of crisis, as confirmed following the 2008 financial crisis.

JEL classification: G01; G21; G28

Keywords: Liquidity risk; Credit risk; Bank risk; Bank; Cohort risk

* Corresponding author *E-mail address:* anup.srivastava@ucalgary.ca

1. Introduction

Rajan (2006) claims that the banking industry has transformed over time because of deregulation and institutional changes, implementation of new capital requirements, financial innovations in off–balance sheet items, integration of markets, and technological advancements. Thakor (2020) describes the implications of new innovations in technology that affect both banking and non-banking financial companies. We examine the associated changes in liquidity and credit risks, the two principal factors in bank failure (Imbierowicz and Rauch, 2014), over 1976–2019 and 1992–2019, respectively. Liquidity risk is the likelihood that a bank would be unable to meet its short-term obligations from assets that can be sold in the short term. It is measured following Berger and Bouwman (2009). Credit risk is the likelihood and the economic importance of client defaults, measured by Basel I risk-weighted assets and off–balance sheet items, scaled by gross total assets (GTA) (following Berger et al., 2016; Berger and Bouwman, 2009; and Khan et al., 2017). We document two stylized facts. The first fact, as illustrated in Fig. 1, is that average liquidity and credit risks of banks have steadily increased over time. While credit risk reversed this trend, and declined for four years after the 2008 financial crisis, its rising trend resumed thereafter, indicating that the brief period of more prudent lending was just an intermittent response to the financial crisis.

[Insert Fig. 1 near here]

The second fact, as illustrated in Fig. 2, is that each new cohort joining the banking industry (proxied by the decade of its start of business) shows higher liquidity and credit risk levels than its predecessor. For this analysis, we call banks that existed before 1970 the pre-1970s cohort and those that started their operations in 1970–1979, 1980–1989, 1990–1999, and 2000–2009 the 1970s, 1980s, 1990s, and 2000s cohort, respectively. Not only does each new cohort start its business at a higher risk level than its predecessor, but the risk differences between successive cohorts also persist, indicating that each successive cohort uses a progressively riskier operating strategy as part of its innate business model and not just as an entrance strategy. We call this progressive increase in risks of successive cohorts the cohort risk phenomenon. Furthermore, risks of all cohorts rise with time, indicating that even legacy banks increase aggressiveness of their operating strategies, which, in combination with the riskier strategies of newcomers, increases overall bank risk.

[Insert Fig. 2 near here]

Prior studies argue that credit and liquidity risks play a significant role in maintaining resilience and stability of the banking system and, consequently, the wider economy. Those risks could adversely affect banks' ability to cope with and even contribute to black swan events, when banks are compelled to unwind their financial positions following a large default or bank run. We demonstrate the downside of riskier business strategies of successive cohorts after a black swan event: the 2008 financial crisis. On one hand, larger credit risks would imply higher default rates by the client. On the other hand, higher liquidity risks would mean that the bank would be unable to meets its short-term obligations. Both could lead to greater likelihood of bank failure. Pre-1970s, 1970s, 1980s, and 1990s cohorts display a progressively higher attrition rate in the two years following the crisis.[1] In 2009–2010, when the impact of the financial crisis was strongly felt, the sample attrition rate for those cohorts was 2.47%, 5.03%, 7.90%, and 8.39%, respectively. Furthermore, this difference in attrition rates between 2009–2010 and a benchmark period of 2001–2007 was higher for newer cohorts than for older cohorts.

[1] We do not include the 2000s cohort for this test, because it was not completely formed yet.

New regulations promulgated over time combined with an onslaught of competition from new fintech companies plausibly could have left banks with little choice but to adopt riskier operating strategies to grow and protect market shares. We consider four factors that might contribute to observed risks: (i) reliance on brokered deposits (instead of on core deposits), (ii) investment in commercial real estate loans, (iii) reliance on off–balance sheet items (e.g., letters of credit and derivate products), and (iv) proportion of noninterest income. We find that successive cohorts of banks pursue more aggressive operational strategies, mirroring the cohort phenomenon in credit and liquidity risks. More important, the inter-cohort differences in risk measures, particularly credit risk, become insignificant once we control for the four operational factors, indicating that the cohort risk phenomenon is largely related to newer cohorts' riskier operational strategies. Of those four factors, commercial real estate loan makes the biggest impact on credit risks, controlling for which by itself turns the cohort pattern in credit risks significant. While we do not imply causation, results at the very least indicate that the newer cohorts increasingly extend commercial real estate loans, as well as show higher credit risks.

We divide our sample into small, medium, and large banks to examine if any systematic variation exists in the cohort risk phenomenon across size categories. The main findings about the cohort risk phenomenon remain qualitatively unchanged. That is, we find both time trends on increase and persistent inter-cohort differences across all three categories. Nevertheless, we find the strongest time trends, but the smallest inter-cohort differences, for large banks. The time trend is lowest for small banks, but the inter-cohort differences are the largest. These contrasting results for large and small banks indicate two things: The average risks of large banks are increasing at a faster rate than for small banks, and the divergence between old cohorts and new cohorts is occurring at a lower rate for large banks than small banks. Stated differently, large banks among old cohorts are adopting riskier strategies and keeping pace with the market much better than smaller banks from the same, old cohorts are. The result that larger, old cohorts are more dynamic in adopting newer operating strategies than smaller, old banks might appear counterintuitive and contrary to the "disruptive innovation" idea in Christensen (1997) but consistent with Gerstner (2003), who said: "Who Says Elephants Can't Dance?" In addition, results support Delis et al. (2014), who find that, after 2004, the risk measures of large banks surpassed the industry average. Arguably, larger banks have the resources, economic size, and capabilities to change and adopt riskier strategies in line with the overall market.

We conduct additional tests by excluding mergers and acquisitions and bank failures, by controlling for two banking crises [the savings and loan (S&L) crisis of the 1980s and 1990s and the financial crisis], and by limiting the sample to "true" commercial banks. We continue to find significant cohort patterns.

Our results provide compelling evidence that the liquidity and credit risk levels of banks have increased in a systematic way over time. This trend is largely due to successive cohorts' progressively high-risk business models. It is also due to increasing risks of large, legacy banks. One plausible explanation for the cohort risk phenomenon is that given saturation in traditional segments and with the emerging competition from technology and non-banking financial sectors, new players keep searching for alternative avenues to fuel growth and to avoid monitoring cost and capital adequacy requirements. A new insight from our study, which may come as a surprise, is that large legacy banks are able to increase risks, keeping pace with the overall industry, while the small legacy banks are not.

Our findings should interest researchers, regulators, and policy makers. Credit and liquidity risks are strongly and independently associated with banks' probabilities of default (Imbierowicz and Rauch, 2014). The Material Loss Reports of the Federal Deposit Insurance Corporation (FDIC) and the Office of the Comptroller of the Currency (OCC) also find liquidity and credit risks to be significant determinants of bank failures.[2] Recent regulatory changes, such as the Basel III framework and its liquidity coverage ratio (LCR) and net stable funding (NSF) ratio, and the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010 propose liquidity stress tests in addition to credit risks. Switzerland-based bank UBS acknowledged in a 2008 report that the main cause for its hefty losses and subsequent financial distress in the wake of the financial crisis was its "funding framework" and "balance sheet management."[3] While post–financial crisis regulations have forced banks to improve their risk-management practices and increase capitalizations, the trends we document do not portend well for the resilience and stability of banking sector (Assaf et al., 2019).

2. Related Literature and Hypotheses Development

The literature on bank risk is extensive and diversified. We limit our review to studies that support the development of our hypotheses. We first describe the significant regulations that affected banking sector during our study period. Then, we summarize the technological developments that have affected or created new opportunities and efficiencies for banks, while raising the spectre of new competition. We offer two hypotheses. The first extends prior literature on time series trends in liquidity and credit risks. The second, which is our main contribution, relates to the cohort phenomenon.

[2] Material Loss Reports are published by the FDIC and OCC whenever a bank default results in a "material loss" to the FDIC insurance fund. On January 1, 2010, the threshold for a material loss to the FDIC fund was raised from $25 million to $200 million. The reports contain a detailed analysis of the failed banks' backgrounds and business models and list the failure reasons.

[3] See *Shareholder Report on UBS's Write-Downs*, UBS AG, Zurich, Switzerland, April 18, 2008, available at https://tinyurl.com/y8k3ym55.

2.1 Regulatory trends

Regulators often impose novel regulations on the banking industry, especially in response to an extreme economic development or crisis. While some regulations impose new restrictions on banks, others remove past restrictions. Certain new laws, aiming to protect a certain set of stakeholders, could even increase moral hazard on the part of regulators, bank managers, or bank shareholders, leading to a reoccurrence of similar crises.

The prominent regulations during our study period are as follows.[4] The Depository Institutions Deregulation and Monetary Control Act of 1980 phased out interest rate ceilings on deposits and raised the deposit insurance ceiling. The Garn–St. Germain Depository Institutions Act of 1982 expanded FDIC powers to assist troubled banks, particularly recapitalization of banks that suffered from interest rate shock after interest rate deregulation. The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 attempted to restore the public's confidence in the savings and loan industry amidst the S&L crisis. It created two new agencies: the Federal Housing Finance Board and the Office of Thrift Supervision. The Crime Control Act of 1990 greatly expanded the authority of federal regulators to combat financial fraud, increased penalties and prison time for those convicted of bank crimes, and gave regulators new procedural powers to recover assets improperly diverted from financial institutions. The Federal Deposit Insurance Corporation Improvement Act of 1991 increased the powers and authority of the FDIC, recapitalized the Bank Insurance Fund, and allowed the FDIC to strengthen the fund by borrowing from the Treasury. The act mandated a prompt resolution to failing banks and ordered the creation of a risk-based deposit insurance assessment scheme. It restricted brokered deposits, solicitation

[4] This section draws from https://www.fdic.gov/regulations/laws/important/.

of deposits, and nonbank activities of insured state banks. It created new supervisory and regulatory examination standards and put forth new capital requirements for banks.

The Housing and Community Development Act of 1992 established a regulatory structure for money laundering and provided regulatory relief to financial institutions. The Riegle–Neal Interstate Banking and Branching Efficiency Act of 1994 permitted adequately capitalized and managed bank holding companies to acquire banks in any state one year after enactment. The Economic Growth and Regulatory Paperwork Reduction Act of 1996 required the Federal Financial Institutions Examination Council and its member agencies to review their regulations at least once every ten years, to identify any outdated or unnecessary regulatory requirements imposed on insured depository institutions.

The Gramm–Leach–Bliley Act of 1999 allowed banks to offer financial services previously forbidden by the Glass–Steagall Act, thereby allowing commercial banks to act as brokers. It allowed affiliations between banks and insurance underwriters. The International Money Laundering Abatement and Financial Anti-Terrorism Act of 2001 required additional record keeping and reporting by financial institutions and greater scrutiny of accounts held for foreign banks and of private banking conducted for foreign persons.

The Sarbanes–Oxley Act of 2002 established the Public Company Accounting Oversight Board to regulate accounting firms that audit publicly traded companies, including banks. It prohibited firms that audit publicly traded companies from providing other services to the companies they audit, and it required that chief executive officers and chief financial officers of publicly traded companies certify annual and quarterly reports. The Federal Deposit Insurance Reform Act of 2005 required the merger of the Bank Insurance Fund and the Savings Association Insurance Fund into the Deposit Insurance Fund. The act also increased the coverage limit for retirement accounts to $250,000 and indexed the coverage limit for retirement accounts to inflation as with the general deposit insurance coverage limit. The Housing and Economic Recovery Act of 2008 focused on housing reform and included provisions addressing foreclosure prevention, community development block grants, and housing counselling. The act established a temporary Federal Housing Administration refinancing program, called the HOPE for Homeowners Program.

The Emergency Economic Stabilization Act of 2008 authorized the United States secretary of the Treasury to spend up to $700 billion to purchase distressed assets, particularly mortgage-backed securities, and supply banks with cash. The Helping Families Save Their Homes Act of 2009 contained provisions intended to prevent mortgage foreclosures and enhance mortgage credit availability. The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 implemented significant changes affecting the oversight and supervision of financial institutions and systemically important financial companies. It also provided the FDIC with new resolution powers for large financial companies, created a new agency (the Consumer Financial Protection Bureau), introduced (for nonbank financial companies) or codified (for bank holding companies) more stringent regulatory capital requirements, and set forth significant changes in the regulation of derivatives, credit ratings, corporate governance, executive compensation, and the securitization market.

2.2 Technological trends

Technological developments have impacted many information-based industries, and banking sector has not been left untouched.[5] On the one hand, technology has helped banks learn about and monitor their clients, cross-sell additional services, reduce expenses on the front and back office, and manage risk more promptly and proficiently. On the other hand, technology has

[5] See Thakor (2020) for a review of literature on fintechs.

enabled many new non-banking competitors to start offering services traditionally offered by banks. For example, a few digital banks have offered high yields and convenience without any branch network, such as Discover Financial and Synchrony Financial. This is a significant threat to banks because of the loss of low-cost funding in a business environment already characterized by low interest rates and yields on the asset side. Fund transfers, a source of high-margin fees for banks, is largely taken over by upstarts such as Paypal, Square, Stripe, Rimity, and Zoom.

Tech giants such as Amazon, Apple, Facebook, Google, and Samsung are working toward online payment and digital wallets services such as AliPay and WeChat. Firms that facilitate transactions on their phones, such as Apple and Samsung, demand a cut from the transactions occurring on their devices. Niche digital players now control a large part of customer relationships for the origination of mortgages (e.g., Lending Tree and Quicken), personal loans (e.g., Lending Club), student loans (Upstart), insurance (The Digital Insurer), retail investing (e.g., Robinhood), and loans to small and medium enterprises (e.g., Kabbage and Fundation). Upstarts such as Aspiration are offering digital banking services while promoting environmental causes, appealing to a growing segment of population opposed to large banks. Amazon is not only facilitating commercial transactions for small business owners but also providing logistical and financing services.

Banks have many structural advantages against these upstarts. They have scale and brand, more stable funding model, and vaster reach, and they touch multiple aspects of their customers that involve finance. In addition, banks comply with myriad regulations that permit them access to deposits and conduct interconnected business activities that nonbanks cannot. Most important, they have long experience and knowledge in managing credit risk, liquidity risk, assets, and liabilities. Nevertheless, the threats emerging from technological front cannot be ignored. In particular, banks can no longer so easily attract talented manpower among new graduates that now prefer to work for fintechs.

2.3 Time trend in liquidity and credit risks

While the technological and regulatory developments do not suggest any monotonic trend in credit and liquidity risks, two studies suggest an increase in those risks over time. Berger and Bouwman (2009) report that liquidity creation by U.S. banks increased significantly between 1993 and 2003. Their evidence contradicts the notion that the role of banks in creating liquidity has declined due to new developments in capital markets. We use a similar measure as Berger and Bouwman (2009), which is essentially a liquidity difference between the asset and liability sides. We interpret that measure as a proxy for liquidity risk because it also represents the bank's inability to meet its creditors' demand in the short term when a bank run or liquidity crisis occurs. Delis et al. (2014) examined various measures of risk for the U.S. banking industry. When risk is measured by risk-weighted assets divided by total assets, they find a steady increase from 1986 to 2007 and a steep decline during the financial crisis. We extend these studies by examining a longer period, thereby covering the post–financial crisis period. Just four years after the financial crisis, the credit risk resumed its rising trend and reached pre–financial crisis levels.

In line with the above discussion, we offer H1.

H1: *Liquidity risk and credit risk levels of the U.S. banking industry have increased over the past few decades.*

2.4 Cohort patterns in liquidity risk and credit risk

Our main contribution to the literature is an investigation of the cohort risk phenomenon, that is, whether changes over time in average bank characteristics are related to systematic differences between the characteristics of successive cohorts joining the industry. Prior studies examine the differences between young and old banks and between small and large banks.

DeYoung and Hasan (1998) finds that new banks are less profit efficient than their established counterparts because of their excess branch capacity, reliance on expensive large deposits, and affiliation with a multibank holding company. In addition, new banks' low profit efficiency is associated with higher variations in profit, suggesting that young banks are riskier than the established banks.

DeYoung (1999) finds that, for the first 12 years of their lifecycle, banks show increasing return on assets and decline in growth. Interestingly, hazard rate, a proxy for bank failure rate, increases during the initial years, peaks at about six years life, and declines thereafter. The study indicates that the first six years are the most difficult years in the life of the bank, but probability of bank failure declines thereafter. DeYoung (2003) shows that new banks and established banks fail for similar operational reasons, but new banks are more sensitive to adverse changes in local market conditions. In general, studies conclude that newer banks are riskier and more likely to fail than their established counterparts.

Delis et al. (2014) examine risk differences, measured by risk-weighted assets divided by GTA, across banks of different size classes. They find that most banks have risk levels very close to the industry's average until 2004. After 2004, the risk dispersion among banks increases. Surprisingly, small and very small banks become less risky than the average, and the risks of large banks surpass the industry average. The very large banks also see their risk increasing considerably after 2002. Delis et al. (2014) indicate that small banks could have become less risky than large banks.

While prior studies examine risk differences across groups based on size and age, no study examines the systematic differences in risks across cohorts. This subtle point can revealed by the following question: Is a bank that began its operations in 1970, and must have stabilized its operations by the time it turned seven years old in 1977 (DeYoung, 1999), be systematically different from banks that began their operations in 1980, 1990, and 2000 and are observed when they were seven years old in 1987, 1997, and 2007, respectively? A related question then arises: Is there a systematic pattern in the characteristics of these successive cohorts? In a non-banking context, Brown and Kapadia (2007), Srivastava (2014), and Srivastava and Tse (2017) find systematic patterns in the business characteristics, firm-specific risks (volatility in stock return that cannot be explained by factor models), and earnings volatility for U.S. corporations. For example, Srivastava and Tse (2017) shows that successive cohorts use persistently higher research and development and compete with more knowledge-based business models.

The theory for systematic differences across cohorts comes from Stinchcombe (1965), who argues that organizations are shaped by technological resources, state of product markets, and market conditions prevalent at the time of their foundation. Once established, organizations may survive far into the future with their founding structures largely intact. Consistent with this idea, Christensen (1997) states that established companies are unable to change at the same pace as the newer cohorts entering their markets, because they are too large to change, do not want to change their business models that proved successful in the past, or do not feel the need to change. So, any time trends in banks' competitive strategies, business models, or market conditions should be reflected in cohort patterns. These theories suggest that each new cohort would readily form and adopt a new business model consistent with the conditions prevalent at the time of its formation. Meanwhile, having established and stabilized their operations, the older cohorts would be unable to change at the same pace as newer cohorts joining the industry (Yip, 2004).[6] That is, each new

[6] Nevertheless, any significant change in business models for banks must require superior talent, large resources, economies of scale, and technological capabilities. For example, changing all tellers to a network of automatic teller machines (ATMs) and replacing a branch network with a comprehensive digital platform would require large investments in technology. Small, struggling banks may not have the resources to carry out this transformation. So, in

cohort should mimic the industry's time patterns in a more pronounced manner than older cohorts over time.

Hence, we offer H2.

H2: *Liquidity and credit risk levels of successive cohorts of banks are persistently higher than their predecessors.*

3. Sample

Our data set includes chartered banks in the United States that have available financial data from 1976 to 2019.[7] We construct financial variables using fourth-quarter data (December 31) from the Bank Regulatory database of Wharton Research Data Services (WRDS). WRDS sources data from the annual Report of Condition and Income (Call Report), which contains balance sheet, income statements, risk-based capital measures, and off–balance sheet data. Due to mergers and acquisitions, new entry, and failures, the data set is an unbalanced panel and consists of 389,434 bank-year observations for 17,822 banks. We impose four requirements for sample selection. First, banks must have non-missing information on gross total assets, total equity capital, total loans, and total deposits. Second, banks must have GTA of more than $25 million, similar to Berger and Bouwman (2009).[8] Third, banks must have been established before 2009 to ensure that our sample contains only settled banks, that is, those that have had enough time to stabilize their operations. Fourth, observations must be made after a cohort is completely formed.

We divide all banks into five cohorts based on their founding year. Banks that started operations before 1970 are considered the benchmark for assessing the risk of subsequent cohorts. They are called the pre-1970s cohort for our analysis. The new banks are the banks that started in

---

contrast to the Christensen (1997) claim, established and successful banks might be better able to change with the times.

[7] The database has quarterly data available from 1976.

[8] Berger and Bouwman (2009) exclude very small banks with average GTA below $25 million and argue that they are not likely to be viable commercial banks in equilibrium.

1970 and onward. They are subsequently split into four ten-year groups: the 1970s cohort that started between 1970 and 1979, the 1980s cohort that started between 1980 and 1989, the 1990s cohort that started between 1990 and 1999, and the 2000s cohort that started between 2000 and 2009. We select the ten-year period as a basis for our cohort formation to be consistent with similar groupings used in non-banking studies (e.g., Brown and Kapadia, 2007; Srivastava, 2014). We find similar patterns by using alternative five-year cohorts, 1980–1984, 1985–1989, and so on (results not tabulated). Because we focus on the stable characteristics of cohorts, we exclude observations corresponding to cohort formation years and retain only the observations after a cohort is completely formed. For example, for the 1980s cohort, we drop intermittent observations from 1981 to 1989 and examine observations only from 1990 to 2019.

Table 1 presents the annual distribution of observations for all banks. The total number of banks drops sharply from around 11,100 in 1976 to around 3,600 in 2019. This fall can be attributed to mergers between banking companies and the consolidation of the banking industry (Berger and Bouwman, 2009) as well as bank failures. Moreover, this decline in number of banks could be associated with banking crises and regulatory changes (Berger et al., 1995). Columns (2) to (6) of Table 1 presents the annual distribution of observations for established (pre-1970s) banks and newer banks (1970s, 1980s, 1990s, and 2000s cohorts). It illustrates that most banks in our sample are pre-1970s, which therefore are used as the benchmark for newer cohorts,

[Insert Table 1 near here]

4. Definition and Measurement of Key Variables

In this section, we discuss key dependent and independent variables.

4.1 Dependent variables

We examine liquidity and credit risks, the two principal factors in probabilities of bank failure (Imbierowicz and Rauch, 2014).

4.1.1 Liquidity risk

We use the liquidity creation indicator introduced by Berger and Bouwman (2009) as a measure of banks' liquidity risk. It has been used as a key measure of liquidity risk in subsequent studies (e.g., Berger et al., 2016; Distinguin et al., 2013; Khan et al., 2017). The advantage of using this indicator is that it combines different sources of liquidity in one measure (Berger and Bouwman, 2016). In addition, it provides information on the liquidity profile, the cash value of assets that could be monetized, and the availability of market funding that could affect bank liquidity (Distinguin et al., 2013). We follow the Berger and Bouwman (2009) three-step procedure to construct this measure. Step 1 classifies a bank based on balance sheet and off–balance sheet activities, as liquid or illiquid. We follow Khan et al. (2017) in ignoring semiliquid activities because these activities produce roughly zero net impact on liquidity creation. Step 2 applies weights to the activities classified in the first step. Step 3 combines the classified and weighted activities in the first and second steps, respectively, to compute the liquidity creation (liquidity risk) measure, which is scaled by GTA as follows:

$$\textit{Liquidity Creation} = [0.5\,(\textit{Illiquid Assets} + \textit{Liquid Liabilities} + \textit{Illiquid Guarantees}) - 0.5\,(\textit{Liquid Assets} + \textit{Illiquid Liabilities} + \textit{Liquid Guarantees and Derivatives})] \,/\, \textit{GTA}. \quad (1)$$

A more detailed description of the liquidity risk measure and its calculation is provided in Appendices 1 and 2, respectively.

4.1.2 Credit risk

Credit risk is defined as the bank's Basel I risk-weighted assets. This is a weighted sum of the bank's assets and off–balance sheet activities, divided by GTA, and it has been used in several banking studies as a measure of bank risk (e.g., Berger et al., 2016; Berger and Bouwman, 2009, 2013; Khan et al., 2017).[9] All banks report their risk-weighted assets in Call Reports from 1990 because Basel I risk-based capital requirements became effective in December 1990.[10] The description of credit risk measure is provided in Appendix 2.

4.2 Independent variables

We investigate several variables that are proxies for banks' operating strategy and could be associated with the two risk measures we examine in this study. All variables are expressed as a ratio with respect to the bank's GTA except noninterest income, which is divided by total operating income. A description of these variables is in Appendix 1.

4.2.1 Brokered deposits

Banks increasingly rely on brokered deposits, instead of core deposits, as a source of their funding (Cole and White, 2012; Berger and Bouwman, 2013). Consequently, we expect successive cohorts of new banks to exhibit an increasing concentration of these deposits. Brokered deposits are expensive and therefore must be invested in high-risk assets to cover their high interest costs (Berger and Bouwman, 2013). As such, brokered deposits are more strongly associated with

[9] According to Berger and Bouwman (2009), dividing the dependent variable by GTA is essential to make it meaningful and comparable across banks and to avoid assigning excessive weight to large banks.

[10] Data are available on the FDIC website, https://www5.fdic.gov/sdi/download_large_list_outside.asp, only from 1992.

failures than with solvent thrifts (Goldberg and Hudgins, 2002).[11] Cole and White (2012) find that brokered deposits increase the likelihood of bank failures. More recently, Berger and Bouwman (2013) conclude that banks, especially small banks, are less likely to survive during a crisis if they have more brokered deposits. *BDGTA* is measured by dividing brokered deposits by GTA.

4.2.2 Commercial real estate loans

Commercial real estate loans are given to finance acquisition, development, and construction of income-producing properties such as retail malls, shopping centers, office buildings and complexes, and hotels, with payback prospects that are highly susceptible to economic volatility. For example, a slowdown in economic activity would increase the vacancy rates in malls and office buildings and cause loan defaults. Berger et al. (1995) describe commercial real estate lending as one of the riskiest and least diversifiable investments for banks. They also show that commercial real estate loans as a percent of gross total assets rose by more than 50%, from 6.3% in 1979 to 9.8% in 1994. This category of loans played a significant role during the 2008 financial crisis. Cole and White (2012) report that commercial real estate loans were one of the main determinants of bank failure. Furthermore, Berger and Bouwman (2013) find that banks, specifically small banks, are more likely to fail if they have commercial real estate loans. *CRELGTA* is measured by dividing commercial real estate loans [construction and land development loans, real estate loans secured by multi-family (five or more) residential properties, and real estate loans secured by nonfarm nonresidential properties] by GTA.

---

[11] The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 and the Federal Deposit Insurance Corporation Improvement Act restricted the acceptance of brokered deposits to well and adequately capitalized banks only.

4.2.3. Off–balance sheet items

Off–balance sheet items are generally classified into lending products (e.g., loan commitments and letters of credit) and derivative products (e.g., futures, options, and swaps) (Angbazo, 1997). Before 1990, banks were not required to hold capital against off–balance sheet activities. As a result, some banks shifted into off–balance sheet activities (Berger et al., 1995). Berger et al. (1995) show that derivatives grew from 1.9% of gross total assets in 1990 to 3.9%. in 1994, even after the implementation of Basel Accord's risk-based capital standards.[12] Off–balance sheet items are used to not only increase profits but also to reduce monitoring costs, avoid capital adequacy requirements, exploit regulatory arbitrage, and elude taxation (Diamond, 1984; Flannery, 1998; Papanikolaou and Wolff, 2014; Pennacchi, 1988). However, these items can increase risk and could effectively cause insurance bodies such as FDIC to subsidize bank operations because the deposit insurance premiums are based on balance sheet assets and do not reflect the incremental risks associated with off–balance sheet items (Angbazo, 1997). This idea is consistent with the moral hazard hypothesis associated with off–balance sheet items (Avery and Berger, 1991). *OBSGTA* is measured by dividing off–balance sheet items (unused commitments on the asset side and derivatives) by GTA.

4.2.4 Noninterest income

According to DeYoung and Torna (2013), the Gramm–Leach–Bliley Act of 1999, which allowed banks to deal with nontraditional activities, accelerated changes in banks' business models and sources of income. For instance, the ratio of noninterest income to operating income for U.S. banks increased from 10% in 1983 to 35% in 2013 (FDIC data). This transition from traditional

[12] The Basel Accord risk-based capital standards were implemented in 1990 to correct the issues that related to the flat rate standards by requiring banks to hold different amounts of capital, depending on the perceived credit risk of different on– and off–balance sheet assets (Berger et al., 1995).

interest income sources has been facilitated by innovations in information, communications, and financial technologies and supported by the need for banks to confront competition from non-banking financial institutions (Demirgüç-Kunt and Huizinga, 2010).

Revenues from these activities tend to be more volatile than the traditional interest-based income (DeYoung and Torna, 2013). De Jonghe (2010) concludes that "the heterogeneity in extreme bank risk is attributed to differences in the scope of non-traditional banking activities: non-interest generating activities increase banks' tail beta." Stiroh (2004) argues that even a small exposure to noninterest income, particularly trading revenue, increases risk. Similarly, Demirgüç-Kunt and Huizinga (2010) find that very risky banks rely more on noninterest income. DeYoung and Torna (2013) report that the probability of distressed bank failure increased with noninterest income from asset-based nontraditional activities such as investment banking, insurance underwriting, and venture capital. *NIIOI* is measured by dividing noninterest income by total operating income (interest and noninterest income).

4.3 Growth and profitability

We measure profitability by return on equity (*ROE*), which is net income divided by total equity. *Growth* is the annual growth rate of gross total assets.[13]

5. Tests of Hypotheses

5.1 Hypothesis 1

To identify the time series trends in banks' risks, we compute the annual averages of liquidity risk for each year from 1976 to 2019 and for credit risk from 1992 to 2019. Column (8) of Table 1 and Panel A of Fig. 1 show that the liquidity risk generally increased over time. The

[13] Both tails of all variables have been winsorized at 1 percentile (growth, profitability, *BDGTA*, liquidity risk, and *OBSGTA*) or 0.01 percentile (*NIIOI*) depending on the extent of outliers. *CRELGTA* and credit risk are not winsorized due to absence of outliers.

average liquidity risk increased steadily from -1.35% in 1976 to 27.93% in 2019. It is higher in each new decade than the previous decade. Column (9) of Table 1 and Panel B of Fig. 1 show that, barring a brief reduction in credit risk for four years after the 2008 financial crisis, the general trend has been of increase: from 57.13% in 1992 to a peak of 70.17% in 2007, decline to 62.90% in 2012, and then increase again to 68.46% in 2019. We calculate a trend rate, that is, the regression coefficient of annual averages on the year variable. The last row of Table 1 shows that the regression coefficients for liquidity and credit risks are significant at 0.767 and 0.317, respectively, both significant at *p*-level better than 0.01. This supports H1 that the liquidity risk and credit risk in banks have increased over time. The trend extends Berger and Bouwman (2009), who report that liquidity creation by U.S. banks increased between 1993 and 2003, and Delis et al. (2014), who examine credit risk.

4.2 Hypothesis 2

We examine the existence of the cohort risk phenomenon by first computing cross-sectional averages of risk measures, operating covariates, growth, and profitability on a cohort-year basis, following prior studies that examine the cohort phenomenon in the non-banking corporate sector (Brown and Kapadia, 2007; Srivastava, 2014; Srivastava and Tse, 2017). This yields a sample that contains 144 cohort-year observations: 44 annual observations for the pre-1970 banks (1976 to 2019), 40 annual observations for the 1970s cohort (1980 to 2019), 30 annual observations for the 1980s cohort (1990 to 2019), 20 annual observations for the 1990s cohort (2000 to 2019), and ten annual observations for the 2000s cohort (2010 to 2019).[14] We then calculate the average for a cohort by averaging its cohort-year averages.

[14] An exception is the ratio of risk-weighted assets, as a proxy for credit risk, which has 114 cohort-year observations (28 annual observations for the pre-1970 banks, 1970s cohort, and 1980s cohort; 20 annual observations for the 1990s cohort; and ten annual observations for the 2000s cohort), because U.S. banks started to report it in Call Reports in 1990.

Panel A of Table 2 reports the averages of growth, profitability, liquidity risk, and credit risk, by cohort. For the pre-1970s, 1970s, 1980s, 1990s, and 2000s cohorts, respectively, the liquidity risk averages (in percentage terms) are 11.4, 18.2, 26.3, 32.9, and 37.4 and the credit risk averages (in percentage terms) are 62.9, 64.9, 66.6, 73.5, and 73.1. These results show a pattern of increasing risks across successive cohorts. We test statistical significance of the differences between the averages of each successive cohort and its predecessor. Panel A of Table 2 shows that the liquidity risk and credit risk levels increase with successive cohorts, except that the difference between the credit risk of the last two cohorts are not significant.

[Insert Table 2 near here]

Growth averages are 7.7%, 11.90%, 11.7%, 14.3%, and 10.2% for the pre-1970s, 1970s, 1980s, 1990s, and 2000s cohorts, respectively, and their *ROE* averages are 10.3%, 8.3%, 8.0%, 5.7%, and 3.3%, respectively. These results indicate that successive cohorts generally have higher growth than the pre-1970 banks and that successive cohorts show declining profitability.

Panel B of Table 2 presents cohort averages and inter-cohort differences in the proxies of operating strategies: brokered deposits (*BDGTA*), commercial real estate loans (*CRELGTA*), off–balance sheet items (*OBSGTA*), and noninterest income (*NIIOI*). The averages increase for successive cohorts, and the inter-cohort differences are significant, except that the last difference for *OBSGTA* and last two differences for *NIIOI* are not significant.

We use cohort-year averages to test H1 more elaborately by estimating the regression

$$Characteristic_{Cohort,Year} = \gamma_0 + \gamma_1 \times Year + \varepsilon_{Cohort,year}, \qquad (2)$$

where *Characteristic* is a measure of risk, calculated on a cohort-year basis. γ_1 captures the time trend. Table 3 reports results for Eq. (2). Column (2) presents results for credit risk; Column (4), for liquidity risk. Both columns show that the time trend is positive for both credit risk (γ_1 is 2.653,

p-value < 0.01) and liquidity risk (γ_1 is 7.402, p-value < 0.01). These results are more formal tests of H1 and show that the overall time series trend in credit and liquidity risk is positive.

[Insert Table 3 near here]

4.2.1 Examining cohort patterns

The overall averages might not be comparable across cohorts because they are calculated over different periods. For example, the average for the 2000s cohort is calculated using only nine years' observations (2011 to 2019), and the average for the established banks is calculated using 44 years' observations (1976 to 2019). Thus, the pre-1970 cohort's average includes the earliest years' observations from the sample period, whose economic characteristics could differ from those of recent years. Thus, the average inter-cohort differences could simply represent the overall time trends.

Fig. 2 alleviates the concern that the pattern of increasing cohort averages is entirely due to time trends. It plots the cross-sectional averages of liquidity risk and credit risk for each cohort by year. It shows three noteworthy trends. First, each new cohort begins at a higher risk level than its predecessor. Second, the lines generally slope upward, indicating that all cohorts become riskier over time. Third, and most important, the lines rarely intersect, demonstrating that each cohort has persistently higher risk than its predecessor. Thus, the risk differences across cohorts are long-lived.

To formally control for overall time trends in examining cohort patterns, we estimate the regression Eq. (3) following Brown and Kapadia (2007) and Srivastava (2014):

$$Characteristic_{Cohort,Year} = \gamma_0 + \gamma_1 \times Year + \gamma_2 \times Dum1970s + \gamma_3 \times Dum1980s + \gamma_4 \times Dum1990s + \gamma_5 \times Dum2000s + \varepsilon_{Cohort,year}, \quad (3)$$

where *Characteristic* is a measure of risk, calculated on a cohort-year basis. γ_1 captures the time trend. *Dum1970s*, *Dum1980*s, *Dum1990s*, and *Dum2000s* are indicator variables that equal one if the cohort-year observation is for the 1970s, 1980s, 1990s, and 2000s cohort, respectively, and zero otherwise. The dummy variable for pre-1970s banks is considered the reference category and, thus, is excluded from Eq. (3). Hence, the coefficients on the dummy variables represent the differences between the average risk of a new cohort and the pre-1970s cohort after controlling for overall time trends. $\varepsilon_{Cohort,year}$ is the error term.

Table 3 reports results for Eq. (3). Column (3) shows that despite controlling for time trends, the coefficients on successive dummies (*Dum1970s*, *Dum1980*s, *Dum1990s*, and *Dum2000s*) are generally increasing: 2.168, 3.701, 8.813, and 8.569, each significant at *p*-level better than 0.01. These results indicate that newer cohorts carry higher credit risk than the pre-1970s banks. The time trend drops from 2.653 in Eq. (2) to 1.469 in Eq. (3), and the adjusted *R*-squared improves from 18.3% in Eq. (2) to 59.45% in Eq. (3), indicating that the overall time trend is significantly related to higher risks of successive cohorts. *F*-tests (*p*-values presented in the lower rows of the table) show that the differences between the coefficients on successive cohort dummies are significant, except for the last two cohorts (1990s and 2000s).

Column (5) presents similar results for liquidity risk. After controlling for the time trends, the coefficients on successive cohort dummies are 6.722, 9.168, 11.927, and 13.507, all significant at *p*-level better than 0.01. Newer cohorts carry higher liquidity risk than the pre-1970s cohort. The time trend drops from 7.402 in Eq. (2) to 5.774 in Eq. (3), and the adjusted *R*-squared improves from 70.61% in Eq. (2) to 87.95% in Eq. (3). Similar to Column (3), *F*-tests show that the differences between the coefficients of successive cohorts are significant, except for the last two cohorts (1990s and 2000s).

This cohort pattern in liquidity and credit risks is our main contribution to the literature, which we call the cohort risk phenomenon.

4.2.2 Controlling for operating strategies

We calculate the cohort averages of brokered deposits, commercial real estate loans, off–balance sheet items, and noninterest income for each cohort by averaging their cohort-year observations. We test differences in averages between the cohorts. Panel B of Table 2 shows that the successive cohorts have increasing brokered deposits of 1.565, 1.492, 1.679, 4.697, and 4.821 and increasing commercial real estate loans of 10.391, 15.138, 22.329, 31.342, and 36.256 (all in percentage terms). The newest cohorts lend almost one-third of their GTA to commercial real estate, which is almost three times more than the pre-1970 banks. Furthermore, except for the last two cohorts, successive cohorts show increasing off–balance sheet items of 5.423, 6.884, 12.041, 15.442, and 13.597 and increasing noninterest income of 6.961, 9.453, 14.542, 13.273, and 11.578 (figures not presented for brevity). In both cases, the values for the 2000s cohort are higher than for the 1990s cohort.

We next examine the association between the cohort phenomenon and banks' operating strategies and by estimating the following equation:

$$
\begin{aligned}
Characteristic_{Cohort,Year} = {} & \gamma_0 + \gamma_1 \times Year + \gamma_2 \times Dum1970s + \gamma_3 \times Dum1980s \\
& + \gamma_4 \times Dum1990s + \gamma_5 \times Dum2000s + \gamma_6 \times BDGTA \\
& + \gamma_7 \times CRLGTA + \gamma_8 \times OBSGTA + \gamma_9 \times NIIOI + \varepsilon_{Cohort,year}. \qquad (4)
\end{aligned}
$$

We examine whether the cohort risk phenomenon attenuates after we control for the proxies for operating strategies. Table 4 presents results after controlling for *BDGTA*, *CRLGTA*, *OBSGTA*, and *NIIOI* one at a time, in Column (3), (5), (7), and (9), respectively (Panel A for credit risk and Panel B for liquidity risk). In Column (2), we present results without the control for any operational factors for ready reference. In Columns (4), (6), (8), (10), and (12), we present the difference in coefficients on cohort dummies because of control for respective operational factors. We also report results for an additional test after controlling for all those factors in the same regression, in Column (11).

[Insert Table 4 near here]

We find several noteworthy results for credit risks. First, the coefficients on cohort dummies become significantly smaller and even change signs. The biggest impact comes from the inclusion of *CRELGTA*. The coefficient of *Dum1970s* changes from 2.168 to -4.282 (a reduction of 6.450), the coefficient of *Dum1980s* changes from 3.701 to -4.416 (a reduction of 8.117), the coefficient of *Dum1990s* changes from 8.813 to -2.440 (a reduction of 11.253), and the coefficient of *Dum2000s* changes from 8.569 to -5.053 (a reduction of 13.622). The monotonicity in coefficients across successive cohorts largely disappears. The adjusted R-squared increases from 59.45% to 87.07%. The results indicate that commercial real estate loans are the most important operating factor in explaining the cohort phenomenon for credit risk, at least among the factors we examine. Another factor that makes a significant reduction in the cohort phenomenon is brokered deposits (*BDGTA*). That is, the F-test of the equality of coefficients of cohort dummies becomes insignificant. Second, of the factors examined, *CRELGTA*, *OBSGTA, BDGTA*, and *NIIOI* explain the cohort phenomenon in decreasing order. Third, the cohort phenomenon is no longer evident once all four factors are considered (Column 11). The adjusted R-squared increases from 59.45% to 93.16%, indicating that any credit risk differences across years within cohorts, and across cohorts, are largely related to the more aggressive operating strategies.

Panel B presents similar tests for liquidity risk. As against credit risk, *OBSGTA* appears to be the biggest factor. After controlling for *OBSGTA*, the coefficient on *Dum1970s* changes from

6.722 to 4.832 (a reduction of 1.890), the coefficient on *Dum1980s* changes from 9.168 to 4.575 (a reduction of 4.593), the coefficient on *Dum1990s* changes from 11.927 to 5.471(a reduction of 6.456), and the coefficient on *Dum2000s* changes from 13.507 to 9.763 (a reduction of 3.744). Commercial real estate is the second most important factor. Nevertheless, the coefficients on cohort dummies remain significant and positive, indicating that newer cohorts have higher risks than pre-1970 banks. Furthermore, inter-cohort differences remain significant at least in some cases. When all four operational strategy proxies are controlled for, the adjusted *R*-squared increases from 87.95% to 96.89%, but the cohort phenomenon is still apparent.

We must emphasize that we do not claim any causation. We do not claim that higher reliance on real estate loans or off–balance sheet items are the main sources for higher credit and liquidity risks. Furthermore, we do not examine an exhaustive list of factors that could lead to higher credit and liquidity risks. Nevertheless, at a minimum, our results should be viewed as correlations between risk measures and banks' operating strategies. Results demonstrate that successive cohorts pursuing riskier operating strategies, such as chasing commercial real estate loans, also display higher risks.

5. Test of Hypotheses by Bank Size

To gain deeper insight into the cohort risk phenomenon, we split our sample by bank size. Generally, theories do not differentiate between banks of different size categories (Berger and Bouwman, 2013). However, because of imperfections in the market, competitive structure, and differential regulatory requirements, bank size could be related to liquidity risk (e.g., Berger and Bouwman, 2009; Kashyap et al., 2002) and credit risk (e.g., Hakenes and Schnabel, 2011; Stiroh, 2004). We follow Imbierowicz and Rauch (2014) to define the bottom 25 percentile of GTA as small banks, the top 25 percentile as large banks, and the rest as medium banks. We then conduct our tests separately for each bank size.

We describe the sample of firms by three size and five cohort categories in Table 5. Large bank sample is dominated by pre-1970 banks. For example, 789 (64%) out of 1,238 large banks in 2019 are pre-1970s, showing that it takes a long time to reach the top bank size. Nevertheless, a nontrivial number of large banks are from the other cohorts. As expected, newer cohorts have more small banks than large banks. For example, the 2010s cohort has 169 small banks and just 60 large banks in 2019. Furthermore, the number of banks in the starting year of a cohort observation decreases across cohorts. The starting number of observations for the 1970s, 1980s, 1990s, and 2000s cohorts in the small bank category, in the years 1980, 1990, 2000, and 2010, respectively, are 662, 615, 293, and 200. This indicates that new banks, which typically start small, are now entering the industry at a lower rate than in past years.

[Insert Table 5 near here]

5.1 Time trends by size

We first estimate Eq. (2) by three size segments. Panels A and B of Fig. 3 present these risks for credit and liquidity risks, respectively. They show several noteworthy patterns. First, large banks have higher liquidity and credit risks than small banks. Second, liquidity risk has been rising steadily and monotonically for all three bank sizes. Third, credit risks have risen, then dropped in unison after the 2008 financial crisis, and then resumed their upward trend. Fourth, the divergence between small and large banks has increased over time, particularly for credit risks.

[Insert Fig. 3 near here]

Table 6 presents the time trends for credit risk (Panel A) and liquidity risk (Panel B). Columns (3), (4), and (5) report that trends in credit risks for small, medium, and large banks are

0.999, 2.743, and 3.219, respectively, and those for liquidity risks are 5.560, 7.415, and 7.820, respectively. All these trends are significant at conventional levels. The strongest trends are observed for the largest segment. That is, the average increase over time in credit and liquidity risks is the highest for the largest banks. Results are also interpretable as showing that a large bank today is more different from a large bank in the 1980s than a small bank today is different from a small bank in the 1980s.

[Insert Table 6 near here]

5.2 Cohort patterns by size segment

Panels A, B, and C, representing small, medium, and large banks, respectively, present cohort patterns for liquidity in Fig. 4 and credit risks in Fig. 5. Successive cohort lines remain largely nonintersecting, indicating that the cohort phenomenon exists for both types of risks across all three bank sizes. Nevertheless, the spread between cohorts stays narrower for large banks than for small banks for both types of risk. Results indicate that older cohorts are better able to keep pace with newer cohorts in the large bank category than in the small bank category.

[Insert Figs. 4 and 5 near here]

To formally examine cohort patterns by size segments, we estimate Eq. (3) by three size segments. Results are presented in Columns (7) to (9) of Table 6 (Panel A for credit risk and Panel B for liquidity risk). Results for all banks are presented in Column (6) for reference. For small banks, as far as credit risk is concerned, the time trend becomes negative after controlling for cohort dummies. The successive cohort dummies have coefficients of -1.310, 2.100, 6.159, and 9.625, which are significantly different from each other. Regarding liquidity risk, the time trend remains significant after controlling for cohort dummies. Successive cohort dummies display increasing coefficients of 3.719, 8.458, 10.331, and 16.037, which are significantly different from each other. These patterns indicate that, within the small bank category, newer cohorts show progressively higher credit and liquidity risk than their older counterparts. So, we find strong evidence of the cohort phenomenon for small banks, that is, successive cohorts remain persistently different from each over time.

We find similar, strong cohort patterns for medium banks. For credit risk, successive cohort dummies show coefficients of 2.168, 3.637, 8.479, and 8.763. For liquidity risk, successive cohort dummies show coefficients of 7.458, 9.749, 12.570, and 14.699. In both cases, the successive coefficients are significantly different from each other except for the last two cohorts. So, we again find evidence for a cohort pattern for medium banks. The time trend remains significant for both credit and liquidity risk.

We do not find significant cohort patterns for large banks, despite finding strong time trends. For credit risk, the successive cohort dummies have positive and significant coefficients of 2.782, 2.409, 7.366, and 5.325, indicating that all new cohorts are riskier than the pre-1970 cohort. Nevertheless, no persistent pattern emerges of differences across cohorts. We find similar results for liquidity risk. Each successive coefficient is positive and significant at 5.860, 5.604, 7.621, and 7.303, with no consistent pattern of increase. Many of the inter-cohort differences, even when positive, are not significant. This result, combined with the strongest time trends for large banks in Eq. (2), which continue to appear in Eq. (3), indicates that the large banks from older cohorts display increasing risks similar to the large banks from newer cohorts.

Results for large banks may be surprising because they demonstrate that large banks from older cohorts keep pace with large banks from newer cohorts (see Panel C of Fig. 4 and Fig. 5), despite theory suggesting that larger organizations are least amenable to changes with times (Christensen, 1997). These results also demonstrate that large banks from older cohorts better adapt to changing market conditions than do smaller banks from the same cohorts. Arguably, changing business models require talent, resources, economies of scale, and technological capabilities that larger old cohorts possess better than smaller old cohorts.

5.3 Cohort patterns by size segment, after controlling for operating strategies

We estimate Eq. (4) by three size segments, while including one proxy for operating strategy at a time. Results for credit and liquidity risks are presented in Panels A and B of Table 7, respectively. We explain just the salient results. As far as credit risks are concerned, controlling for commercial real estate loans has the biggest impact. The *R*-squared increases from 63.24% to 75.05% for small banks, from 56.40% to 87.21% for medium banks, and from 49.70% to 76.76%, for large banks. Coefficients on most cohort dummies largely turn negative, and the pattern of significant, positive inter-cohort differences disappears in most instances. Results are consistent with the idea that successive cohorts' greater reliance on commercial real estate loans is associated with increased credit risks for all bank sizes. Controlling for all operational factors together turn time trends and cohort dummies negative across all size categories with substantial increase in *R*-squared values.

[Insert Table 7 near here]

Results for liquidity risk are less profound. No single factor leads to a large improvement in *R*-squared or causes a complete disappearance of time series trends. Commercial real estate loans significantly reduce cohort patterns for large banks, indicating that large older cohorts keep increasing their reliance on commercial loans, similar to large new cohorts. When all operating factors are controlled [Columns (14), (15), and (16)], the cohort pattern completely disappears for small bank, and time trend becomes insignificant for medium and large banks. This suggests that changing operating strategies across cohorts and over time significantly explain the cohort trends for small banks and the time trend in liquidity risk for large banks.

6. Impact of Negative Shocks on Bank Failures across Cohorts

Imbierowicz and Rauch (2014) claim that credit and liquidity risks are associated with the likelihood of bank failure. Because each new cohort displays progressively higher credit and liquidity risks, the survival rate should be lower for successive cohort. We find results consistent with this idea, reported in Panels A and B of Fig. 6, which plot the number of banks in each cohort over time.[15] The compound annual diminishment rate (CADR) or the downward slope is a measure of attrition rate over time, resulting from bank failures, mergers, or acquisition (Berger et al. 1999). CADR for successive cohorts are 2.57%, 4.94%, 6.06%, 6.49%, and 7.07%, indicating that pre-1970 banks have the highest survival rate, and that the latest cohort has an attrition rate that is about thrice larger than the pre-1970 banks. This pattern is consistent with the idea that successive bank cohorts, which have higher liquidity and credit risks, have higher failure or attrition rates than their predecessors. (Alternatively, each new cohort could get acquired at a faster rate than its predecessor.) This pattern could be related to different bank sizes. However, the last row of Table 5 shows that the CADRs increase across successive cohorts, even after controlling for bank size, except for large banks, for which no clear pattern is evident.

[Insert Fig. 6 near here]

Aggressive business strategies might fuel growth during boom times but could backfire during the downturns. Prior literature argues (Imbierowicz and Rauch, 2014; Acharya and Mora, 2015) that credit and liquidity risks would particularly exacerbate the failure likelihood of banks during a negative shock to the wider economy. On one hand, the bank would face large-scale client

[15] We plot two different figures because the number of pre-1970 observations is an order of magnitude higher than the other cohorts.

defaults. On the other hand, they would find difficult meeting their own short-term obligations. We test this idea following the black swan event of the 2008 financial crisis, which witnessed large-scale client defaults, particularly in the real estate sector, as well as enhanced difficulty for banks to raise new capital. We report cohort-wise attrition rates for years 2009–2010 in Panel A of Fig. 7 and compare them with the benchmark period before the crisis of 2001–2007 in Panel B. Attrition rate is defined as the decline in the number of sample firms from a given cohort in a particular year divided by the beginning-of-the-year number of banks in that cohort. Fig. 7 shows that pre-1970s, 1970s, 1980s, and 1990s cohorts display an attrition rate during 2009–2010 of 2.47%, 5.03%, 7.90%, and 8.39%, respectively. The corresponding figures for 2001–2007 are 2.84%, 4.75%, 6.18%, and 6.01%. The differences between the two periods increase with successive cohorts, -0.37%, 0.27%,1.71%, and 2.37%, indicating that the failure rates for riskier banks get exaggerated during a black swan event.

[Insert Fig. 7 near here]

Our main results on the cohort risk phenomenon are further robust to exclusion of mergers and acquisitions and bank failures, controlling for two major banking crises reported in recent literature, limiting our sample to "true" commercial banks, and an alternative cohort period specification of five years (results not tabulated).

7. Conclusion

We examine time series changes in two proxies of banks risk, namely, liquidity and credit risks, that are associated with bank failures. We find a steady increase in liquidity risk over the last forty years or so. Credit risk also increases but declines briefly after the 2008 fiscal crisis and rises again to almost the pre-crisis level. We contribute to the literature by showing that this time trend is due to both more aggressive business strategies adopted by newer bank cohorts and increasing risks of legacy banks. In addition, this pattern is related to riskier operating strategies adopted by all banks, but more so by newer cohorts, that is, their enhanced reliance on brokered deposits, commercial real estate loans, off–balance sheet items, and noninterest income. Commercial real estate loans appear to be the strongest factor for the time trends and cohort patterns in credit risk.

We conduct additional tests by dividing banks into small, medium, and large categories. We find significant time trends of increasing risks and the cohort risk phenomenon in all three categories. Examination across categories leads to new insights. The average risks of large banks are increasing at a faster rate than for small banks. Furthermore, large banks from old cohorts are adopting riskier strategies and keeping pace with the market much better than smaller banks from the old cohorts are. These result run contrary to the idea that large established firms are slowest to change over time. Results indicate that larger banks with the resources and capabilities to change are better at keeping pace with the market.

References

Acharya, V. V., Mora, N., 2015. A crisis of banks as liquidity providers. J. Financ. 70 (1), 1–43.

Angbazo, L., 1997. Commercial bank net interest margins, default risk, interest-rate risk, and off–balance sheet banking. J. Bank. Financ. 21 (1), 55–87.

Assaf, A. G., Berger, A.N., Roman, R.A., Tsionas, M. G., 2019, Does efficiency help banks survive and thrive during financial crises? J. Bank. Fin. 106: 445–470.

Avery, R.B., Berger, A.N., 1991. Loan commitments and bank risk exposure. J. Bank. Financ. 15 (1), 173–192.

Berger, A.N., Bouwman, C.H.S., 2009. Bank liquidity creation. Rev. Financ. Stud. 22 (9), 3779–3837.

Berger, A.N., Bouwman, C.H.S., 2013. How does capital affect bank performance during financial crises? J. Financ. Econ. 109 (1), 146–176.

Berger, A.N., Bouwman, C.H.S., 2016. Bank Liquidity Creation and Financial Crises. Academic Press, London, UK.

Berger, A.N., Bouwman, C.H.S., Kick, T., Schaeck, K., 2016. Bank liquidity creation following regulatory interventions and capital support. J. Financ. Intermed. 26, 115–141.

Berger, A. N., Demsetz, R. S., Strahan, P. E., 1999, The consolidation of the financial services industry: Causes, consequences, and implications for the future, J. Bank. Fin. 23(2–4): 135–194,

Berger, A., Kashyap, A. Scalise, J., 1995. The transformation of the U.S. banking industry: what a long, strange trip it's been', Brookings Papers on Economic Activity, vol. 2, pp. 55-218

Brown, G., Kapadia, N., 2007. Firm-specific risk and equity market development. J. Financ. Econ. 84, 358–388.

Christensen, C.M., 1997. The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail. Harvard Business School Press, Boston, MA.

Cole, R.A., White, L.J., 2012. Déjà vu all over again: The causes of U.S. commercial bank failures this time around. J. Financ. Serv. Res. 42 (1–2), 5–29.

De Jonghe, O., 2010. Back to the basics in banking? A micro-analysis of banking system stability. J. Financ. Intermed. 19 (3), 387–417.

Delis, M.D., Hasan, I., Tsionas, E.G., 2014. The risk of financial intermediaries. J. Bank. Financ. 44, 1–12.

Demirgüç-Kunt, A., Huizinga, H., 2010. Bank activity and funding strategies: The impact on risk and returns. J. Financ. Econ. 98 (3), 626–650.\

DeYoung, R., 1999. The birth, growth, and life or death of newly chartered commercial banks. Federal Reserve Bank of Chicago Economic Perspectives 23, no. 3: 18–35.

DeYoung, R., 2003. De novo bank exit. J. Money, Credit, Bank. 35, 711–728.

DeYoung, R., Hasan, I., 1998. The performance of de novo commercial banks: A profit efficiency approach. J. Bank. Financ. 22 (5), 565–587.

DeYoung, R., Torna, G., 2013. Nontraditional banking activities and bank failures during the financial crisis. J. Financ. Intermed. 22 (3), 397–421.

Diamond, D.W., 1984. Financial intermediation and delegated monitoring. Rev. Econ. Stud. 51 (3), 393-414.

Distinguin, I., Roulet, C., Tarazi, A., 2013. Bank regulatory capital and liquidity: Evidence from U.S. and European publicly traded banks. J. Bank. Financ. 37 (9), 3295–3317.

Flannery, M.J., 1998. Using market information in Prudential Bank supervision: A review of the

U.S. empirical evidence. J. Money, Credit, Bank. 30 (3), 273–305.
Gerstner, L.V., 2003. Who Says Elephants Can't Dance? Leading a Great Enterprise through Dramatic Change. HarperBusiness, New York.
Goldberg, L.G., Hudgins, S.C., 2002. Depositor discipline and changing strategies for regulating thrift institutions. J. Financ. Econ. 63 (2), 263–274.
Hakenes, H., Schnabel, I., 2011. Bank size and risk taking under Basel II. J. Bank. Financ. 35 (6), 1436–1449.
Imbierowicz, B., Rauch, C., 2014. The relationship between liquidity risk and credit risk in banks. J. Bank. Financ. 40, 242–256.
Kashyap, A.K., Rajan, R., Stein, J.C., 2002. Banks as liquidity providers: An explanation for the coexistence of lending and deposit taking. J. Financ. 57 (1), 33–73.
Khan, M.S., Scheule, H., Wu, E., 2017. Funding liquidity and bank risk taking. J. Bank. Financ. 82, 203–216.
Papanikolaou, N., Wolff, C., 2014. The role of on– and off–balance sheet leverage of banks in the late 2000s crisis. J. Financ. Stab. 14, 3–22.
Pennacchi, G.G., 1988. Loan sales and the cost of bank capital. J. Financ. 43 (2), 375–396.
Rajan, R.G., 2006. Has finance made the world riskier? Eur. Financ. Manag. 12 (4), 499–533.
Srivastava, A., 2014. Why have measures of earnings quality changed over time? Journal of Accounting and Economics. 57:196–217.
Srivastava, A. and S. Tse., 2016. Why are successive cohorts of listed firms persistently riskier? Eur. Financ. Manag. 22(5): 957–1000.
Stiroh, K.J., 2004. Diversification in banking: Is noninterest income the answer? J. Money, Credit, Bank. 36 (5), 853–882.
Stinchcombe, A. L. 1965., Social structure and organizations. In Handbook of Organizations, edited by James G. March. 142–193. Chicago: Rand McNally.
Thakor, A., 2020. Fintech and banking: What do we know? J. Financ. Intermed. 41 (C).
Yip, G.S., 2004. Using strategy to change your business model. Bus. Strategy Rev. 15 (2), 17–24.

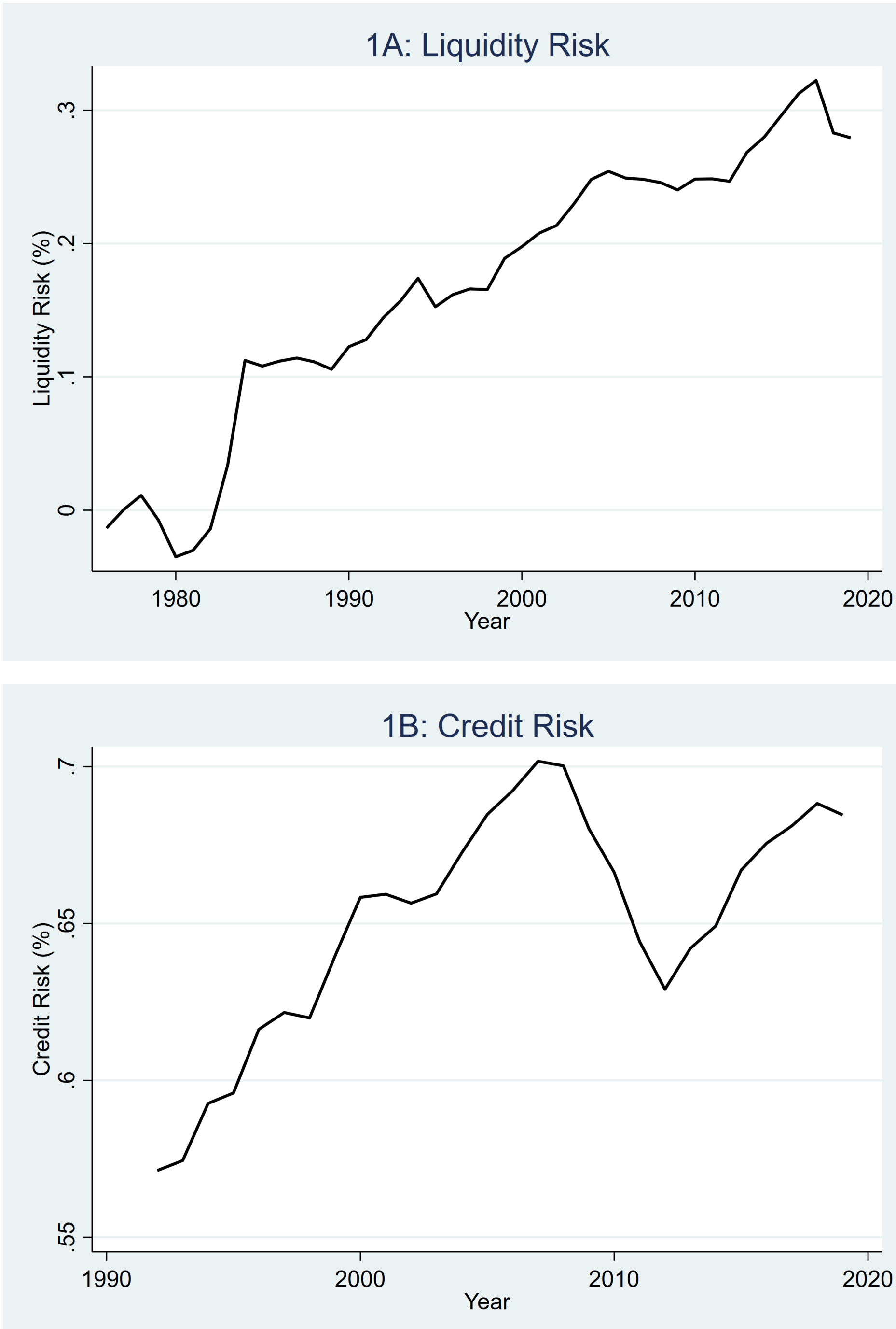


Fig. 1. Time series trend in banks' liquidity and credit risks
This figure illustrates the annual averages of liquidity risk (1A) and credit risk (1B) for U.S. banks. All variables are defined in Appendices 1 and 2.

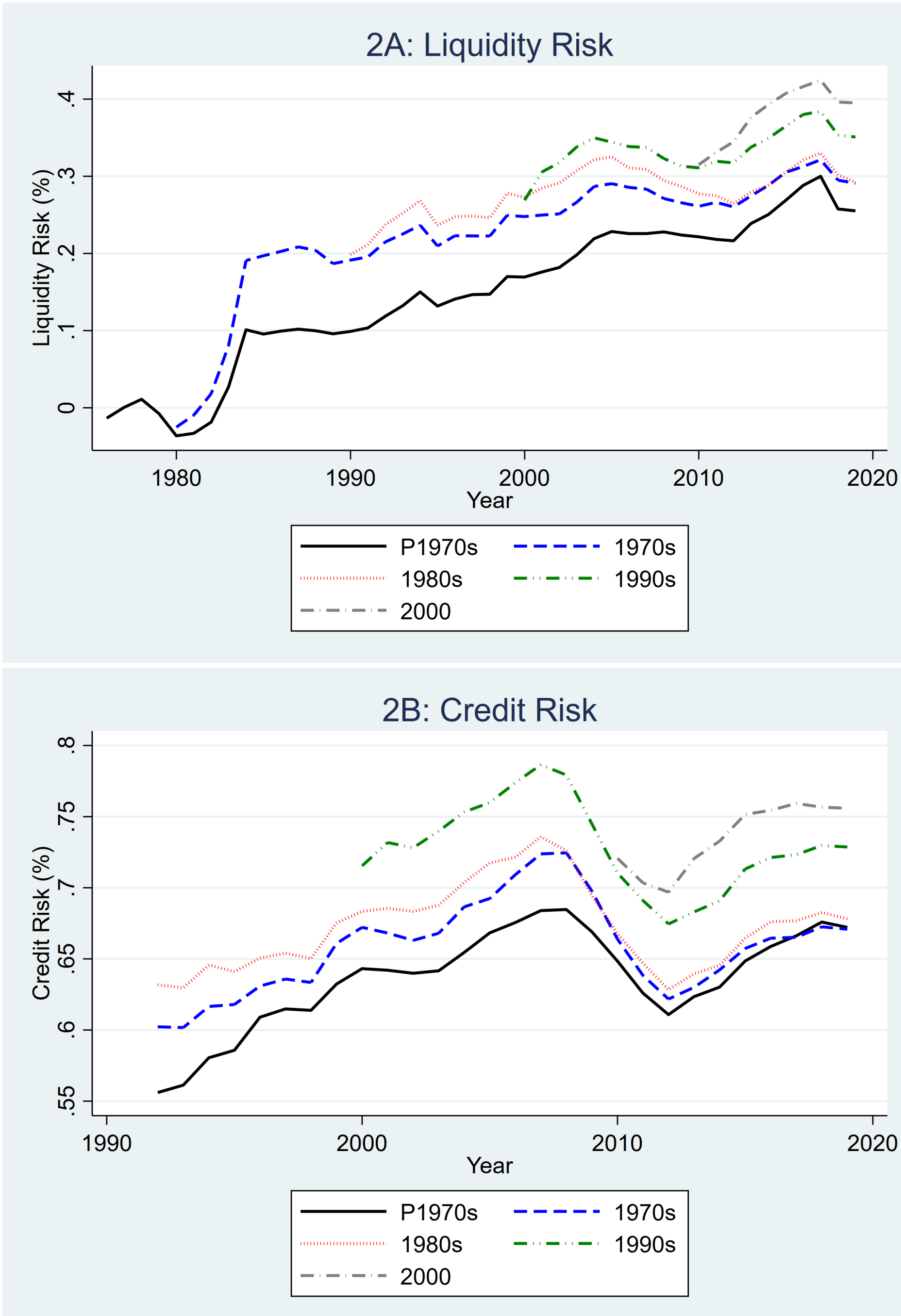
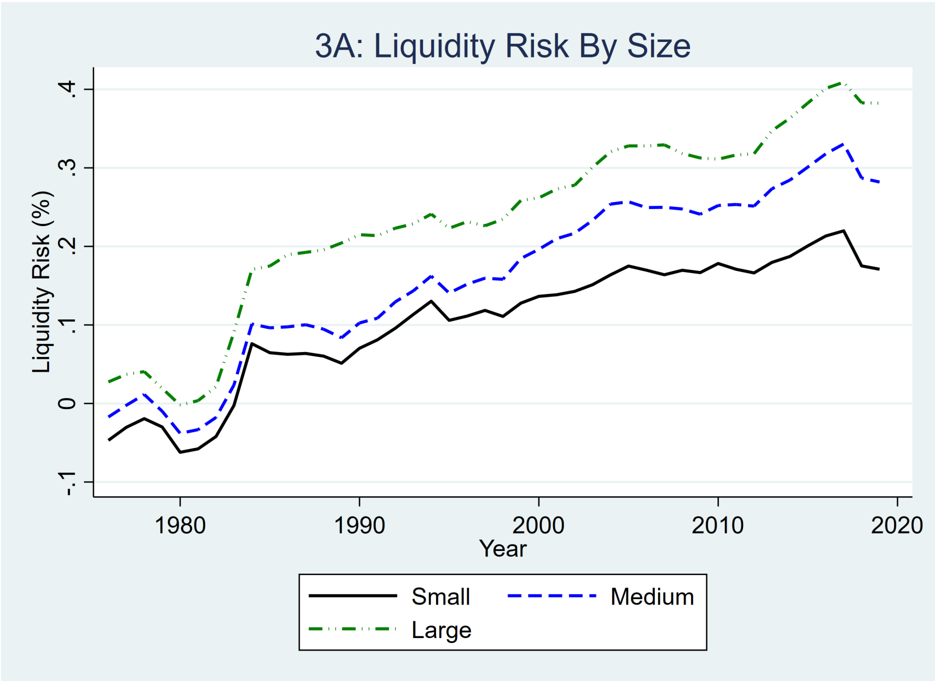


Fig. 2. Cohort trends in banks' credit and liquidity risks

This figure shows cohort trends of liquidity risk (2A) and credit risk (2B) for U.S. banks. The banks are sorted into five cohorts based on their year of opening. All banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as new banks. All banks opened in a common decade are considered part of the same cohort. Consequently, all banks are categorized as pre-1970s banks (P1970s) or a cohort from the 1970s, 1980s, 1990s, or 2000s. This figure presents the annual averages of liquidity risk and credit risk by cohorts. All variables are defined in Appendices 1 and 2.



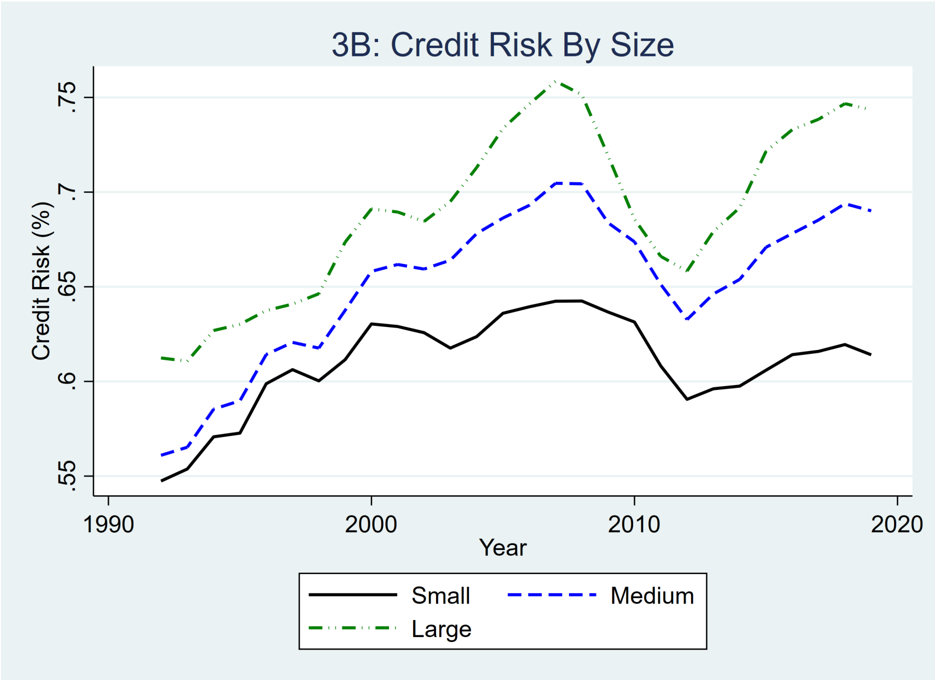
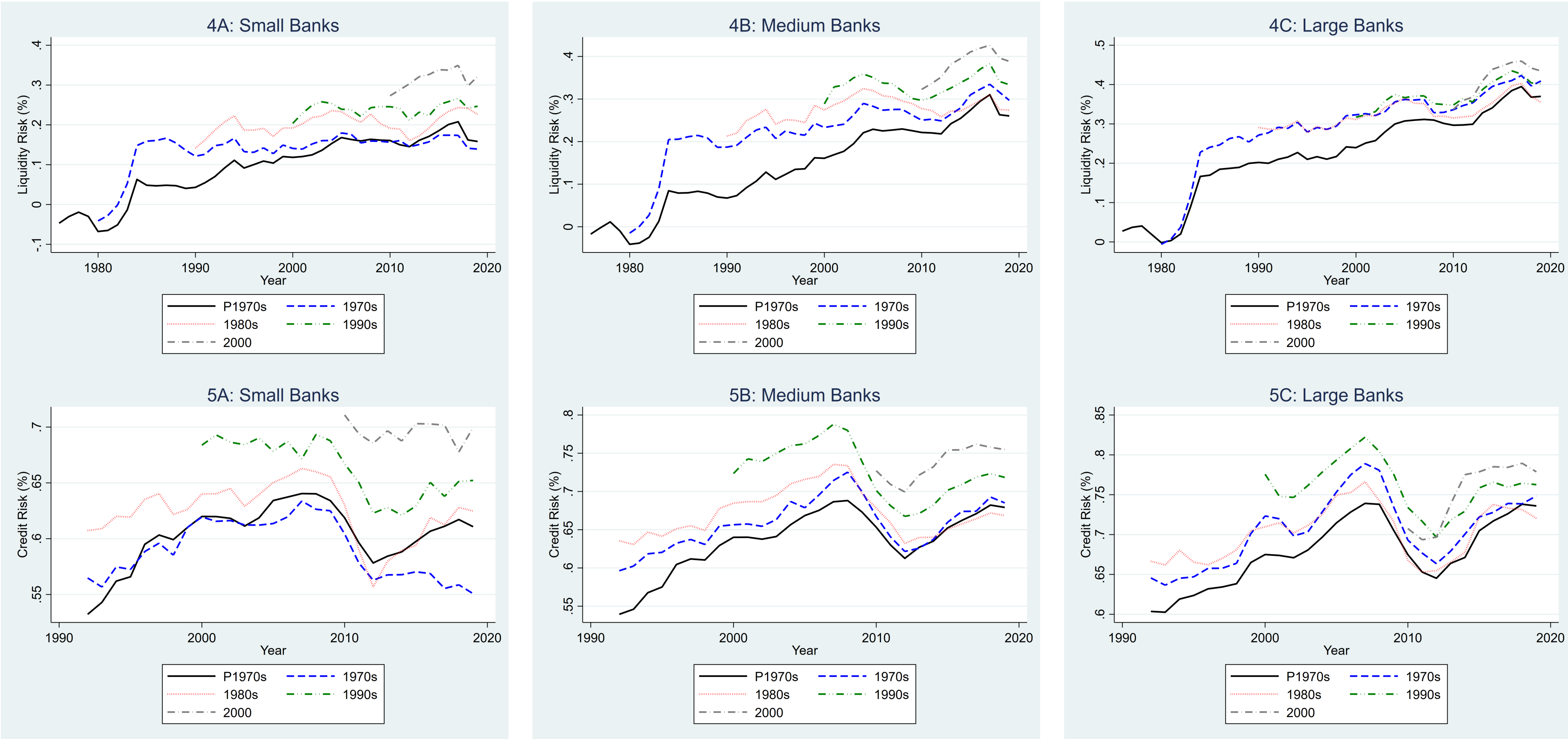


Fig. 3. Time series trends in banks' liquidity and credit risks by size categories

We consider banks in the bottom 25 percentile of gross total assets (GTA) as small banks, those in the top 25 percentile as large banks, and the rest as medium banks. This figure illustrates the annual averages of liquidity risk (3A) and credit risk (3B) for small, medium, and large banks. All variables are defined in Appendices 1 and 2.



Figures 4 and 5. Cohort trends in banks' liquidity and credit risks by size categories

We consider banks in the bottom 25 percentile of gross total assets (GTA) as small banks, those in the top 25 percentile as large banks, and the rest as medium banks. Banks are further sorted into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks (P1970s). The remaining banks are classified as new banks. All banks opened in a common decade are considered part of the same cohort. Consequently, all banks are categorized as pre-1970s banks or a cohort from the 1970s, 1980s, 1990s, or 2000s. This figure illustrates the annual cohort averages of liquidity risk (4) and credit risk (5) for small, medium, and large banks on annual basis. All variables are defined in Appendices 1 and 2.

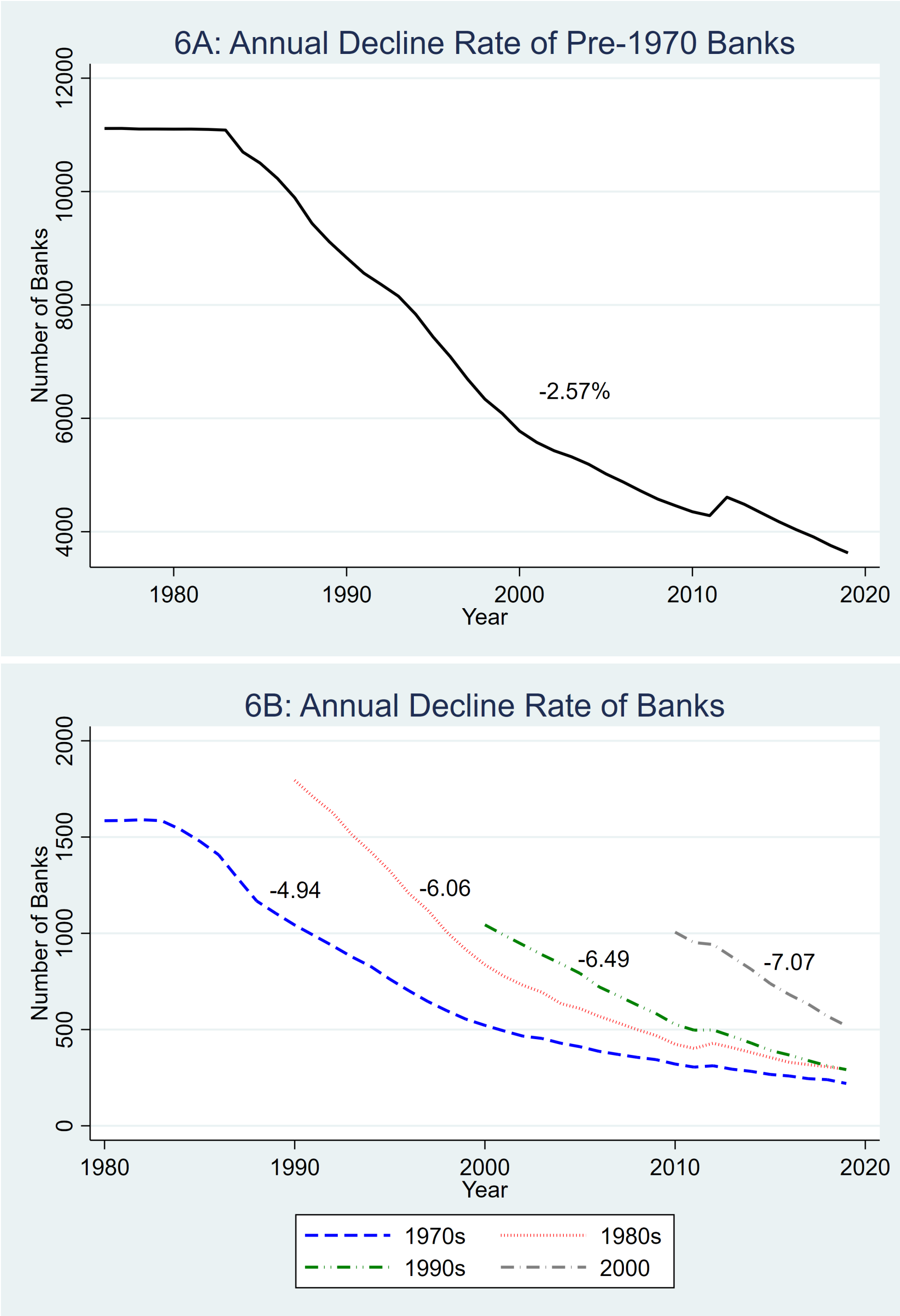


Fig. 6. Cohort-wise compound annual decline rate of banks

Banks are divided into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as new banks. All banks opened in a common decade are considered part of the same cohort. Consequently, all banks are categorized as pre-1970s banks (P1970s) or a cohort from the 1970s, 1980s, 1990s, or 2000s. This figure illustrates the number of bank observations per year. The sample attrition rate is measured by compound annual decline rate (CADR). (6A) presents the numbers of banks and CADR of the pre-1970s cohort, and (6B) presents the numbers of banks and CADR for the 1970s, 1980s, 1990s, and 2000s cohorts.

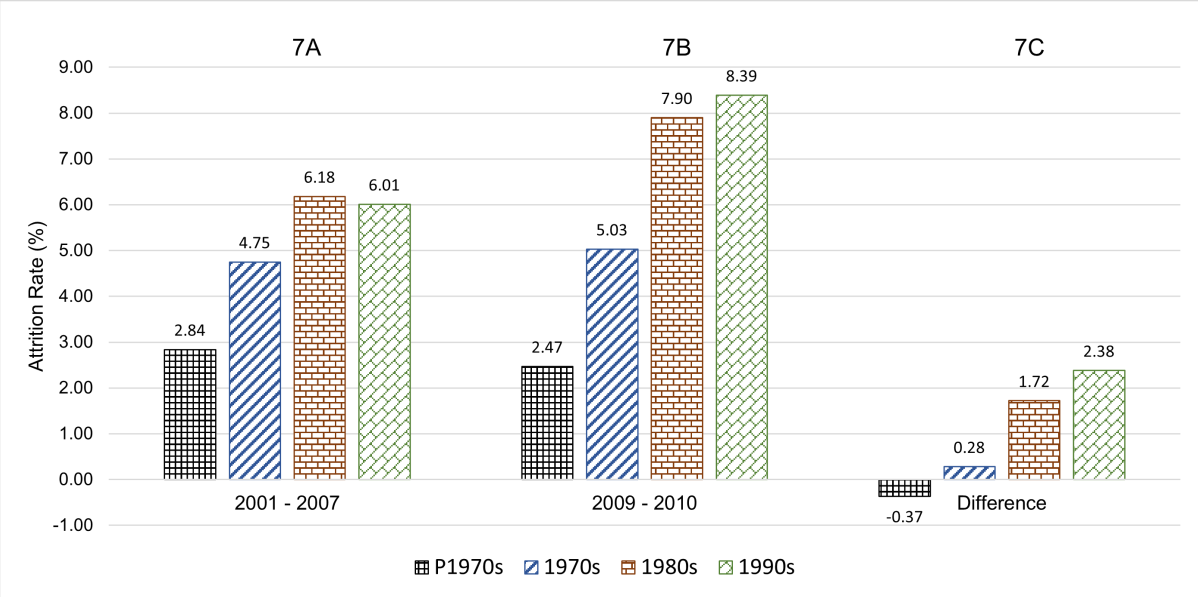


Fig. 7. Cohort-specific sample attrition rate following the 2008 financial crisis

Banks are divided into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as new banks. All banks opened in a common decade are considered part of the same cohort. Consequently, all banks are categorized as pre-1970s (P1970s) banks or a cohort from the 1970s, 1980s, or 1990s. (The 2000s cohort is not included in the analysis because it was not formed by 2008.) These figures (7A and 7B) illustrate the attrition rate (decline in the number of banks in each cohort divided by the number of banks in the cohort at the beginning of that year) for each cohort of banks: 7A for a benchmark period of 2001–2007, and 7b for post-2008-crisis years of 2009 and 2010,. 7C presents the difference between the attrition rates. presented in 7B and 7A.

Table 1
Sample description

Banks are divided into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as a cohort from the 1970s, 1980s, 1990s, or 2000s based on the decade of their opening year. This table reports the annual number of banks by cohorts as well as the annual averages of liquidity risk and credit risk. All variables are defined in Appendices 1 and 2. CADR is the compound annual decline rate. Trend rate is the regression coefficient of the year variable.

Annual observations by cohorts						Annual averages of risks		
Year	Pre-1970 banks	1970s cohort	1980s cohort	1990s cohort	2000s cohort	Observations	*Liquidity Risk* (%)	*Credit Risk* (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1976	11,113					11,113	-1.35	
1977	11,114					11,114	0.05	
1978	11,103					11,103	1.10	
1979	11,103					11,103	-0.75	
1980	11,101	1,585				12,686	-3.50	
1981	11,102	1,586				12,688	-3.01	
1982	11,096	1,590				12,686	-1.40	
1983	11,085	1,585				12,670	3.38	
1984	10,698	1,539				12,237	11.24	
1985	10,502	1,479				11,981	10.81	
1986	10,232	1,408				11,640	11.18	
1987	9,893	1,286				11,179	11.42	
1988	9,439	1,168				10,607	11.13	
1989	9,115	1,104				10,219	10.57	
1990	8,834	1,043	1,795			11,672	12.26	
1991	8,560	989	1,706			11,255	12.80	
1992	8,361	935	1,626			10,922	14.45	57.13
1993	8,154	878	1,513			10,545	15.72	57.45
1994	7,835	828	1,423			10,086	17.40	59.27
1995	7,437	762	1,324			9,523	15.25	59.60
1996	7,087	702	1,208			8,997	16.16	61.63
1997	6,691	646	1,120			8,457	16.60	62.16
1998	6,338	598	1,006			7,942	16.54	62.00
1999	6,087	554	915			7,556	18.89	63.96
2000	5,776	522	837	1,044		8,179	19.77	65.83
2001	5,576	493	777	991		7,837	20.78	65.93
2002	5,429	466	730	940		7,565	21.36	65.65
2003	5,323	454	694	889		7,360	22.96	65.95
2004	5,190	429	635	842		7,096	24.80	67.26
2005	5,020	411	609	792		6,832	25.42	68.48
2006	4,877	387	569	722		6,555	24.91	69.24
2007	4,721	371	535	676		6,303	24.82	70.17
2008	4,575	356	500	628		6,059	24.58	70.03
2009	4,462	344	469	583		5,858	24.03	68.03
2010	4,352	321	424	527	1,006	6,630	24.84	66.63
2011	4,284	305	402	497	952	6,440	24.85	64.43
2012	4,609	312	429	498	942	6,790	24.67	62.90
2013	4,484	294	406	465	877	6,526	26.84	64.21
2014	4,330	283	381	430	813	6,237	27.98	64.92
2015	4,177	267	355	392	739	5,930	29.64	66.70
2016	4,037	259	330	368	682	5,676	31.26	67.56
2017	3,909	245	318	339	632	5,443	32.24	68.11
2018	3,756	240	307	312	570	5,185	28.30	68.83
2019	3,627	220	293	292	520	4,952	27.93	68.46
CADR	-2.57%	-4.94%	-6.06%	-6.49%	-7.07%			
Trend rate							0.767 ($p < 0.01$)	0.317 ($p < 0.01$)

Table 2

Average financial characteristics of successive cohorts of banks and inter-cohort differences

Banks are divided into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as a cohort from the 1970s, 1980s, 1990s, or 2000s based on the decade of their opening year. This table reports the overall cohort averages (calculated by averaging the cohort-year averages) and significance of differences across cohorts. Number of observations by cohort year are presented in Table 1. All variables are defined in Appendices 1 and 2. The superscripts a, b, and c indicate significance at a *p*-level of 0.01, 0.05, and 0.10, respectively.

Panel A: Cohort-wise averages characteristics and risks and inter-cohort differences								
Cohort	*Growth*		*Profitability*		*Credit Risk*		*Liquidity Risk*	
(1)	(2)		(3)		(4)		(5)	
	Average × 100	Inter-cohort difference	Average × 100	Inter-cohort difference	Average × 100	Inter-cohort difference	Average ×100	Inter-cohort difference
Pre-1970	7.700		10.292		62.900		11.364	
1970s	11.924	4.224[a]	8.289	- 2.003[a]	64.952	2.051[a]	18.209	6.844[a]
1980s	11.748	-0.176[a]	8.002	-0.287[a]	66.636	1.684[a]	26.330	8.122[a]
1990s	14.273	2.525[a]	5.785	-2.217[a]	73.490	6.854[a]	32.896	6.566[a]
2000s	10.225	-4.048[a]	3.261	- 2.524[a]	73.108	-0.382[a]	37.381	4.485[a]
Observations	389,434		389,269		203,481		389,434	

Panel B: Cohort-wise averages of banks' operating characteristics and inter-cohort differences								
Cohort	*BDGTA*		*CRELGTA*		*OBSGTA*		*NIIOI*	
	Average × 100	Inter-cohort difference	Average × 100	Inter-cohort difference	Average × 100	Inter-cohort difference	Average × 100	Inter-cohort difference
Pre-1970	1.565		10.391		5.423		6.961	
1970s	1.492	-0.072[a]	15.138	4.747[a]	6.884	1.461[a]	9.453	2.492[a]
1980s	1.679	0.187[a]	22.329	7.191[a]	12.041	5.157[a]	14.542	5.088[a]
1990s	4.697	3.018[a]	31.342	9.013[a]	15.442	3.401[a]	13.273	-1.268[a]
2000s	4.821	0.124[a]	36.256	4.915[a]	13.597	-1.845[a]	11.578	-1.696[a]
Observations	389,434		389,434		389,434		389,434	

Table 3

Time series and cohort trends in bank risks

Banks are divided into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as a cohort from the 1970s, 1980s, 1990s, or 2000s based on the decade of their opening year. Each observation is a cohort-year average, yielding a sample that contains 144 cohort-year observations: 44 annual observations for the pre-1970 banks (1976 to 2019), 40 annual observations for the 1970s cohort (1980 to 2019), 30 annual observations for the 1980s cohort (1990 to 2019), 20 annual observations for the 1990s cohort (2000 to 2019), and ten annual observations for the 2000s cohort (2010 to 2019). For credit risk, we use 114 cohort-year observations (28 annual observations for the pre-1970 banks, 1970s cohort, and 1980s cohort). We estimate the regression

$$Risk_{cohort,\,year} = \beta_0 + \beta_1 \times Year + \gamma_1\, Dum1970s + \gamma_1\, Dum1980s + \gamma_2\, Dum1990s + \gamma_3\, Dum2000s + \varepsilon_{cohort,\,year},$$

where *Risk* is the liquidity risk (or credit risk) calculated on a cohort-year basis. *Dum1970s, Dum1980s, Dum1990s,* and *Dum2000s* are dummy variables equal to one if the cohort-year observations are for the 1970s, 1980s, 1990s, and 2000s cohort, respectively, and zero otherwise. The dummy variable for pre-1970s banks is considered the reference category and, therefore, is excluded. ε is the error term. All coefficients are multiplied by 100 (except coefficient on *Year*, called time trend, is multiplied by 1,000). All variables are defined in Appendices 1 and 2. The superscripts a, b, and c indicate significance at the *p*-level of 0.01, 0.05, and 0.10, respectively. *Opposite* in *F*-test indicates that the difference in coefficients is opposite to expectation.

Variable	*Credit Risk*		*Liquidity Risk*	
	Time trend	Time trend and cohorts	Time trend	Time trend and cohorts
(1)	(2)	(3)	(4)	(5)
Year	2.653[a]	1.469[a]	7.402[a]	5.774[a]
Dum1970s		2.168[a]		6.722[a]
Dum1980s		3.701[a]		9.168[a]
Dum1990s		8.813[a]		11.927[a]
Dum2000s		8.569[a]		13.507[a]
Constant	59.108[a]	59.153[a]	3.597[a]	1.680[a]
Observations	114	114	144	144
F-value	26.31[a]	34.14[a]	344.51[a]	209.68[a]
Adjusted R^2	18.30%	59.45%	70.61%	87.95%
F-test of difference in coefficients on cohort dummies (*p*-values presented)				
1970s > Pre-1970s ($\gamma_1 > 0$)		0.009		0.000
1980s > 1970s ($\gamma_2 > \gamma_1$)		0.064		0.006
1990s > 1980s ($\gamma_3 > \gamma_2$)		0.000		0.009
2000s > 1990s ($\gamma_4 > \gamma_3$)		*Opposite*		0.256

Table 4

Time series and cohort trend in bank risks, after controlling for operating characteristics

Banks are divided into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as a cohort from the 1970s, 1980s, 1990s, or 2000s based on the decade of their opening year. Each observation is a cohort-year average, yielding a sample that contains 144 cohort-year observations: 44 annual observations for the pre-1970 banks (1976 to 2019), 40 annual observations for the 1970s cohort (1980 to 2019), 30 annual observations for the 1980s cohort (1990 to 2019), 20 annual observations for the 1990s cohort (2000 to 2019), and ten annual observations for the 2000s cohort (2010 to 2019). For credit risk, we use 114 cohort-year observations (28 annual observations for the pre-1970 banks, 1970s cohort, and 1980s cohort). We estimate the regression

$$Risk_{cohort,\ year} = \beta_0 + \beta_1 \times Year + \beta_2 \times Characteristic_{cohort;\ year} + \gamma_1\ Dum1970s + \gamma_1\ Dum1980s + \gamma_2\ Dum1990s + \gamma_3\ Dum2000s + \varepsilon_{cohort,\ year},$$

where *Risk* is the liquidity risk (or credit risk) calculated on a cohort-year basis. *Characteristic* refers to the average of one of the bank-specific factors (brokered deposits, commercial real estate loans, off–balance sheet items, or noninterest income) calculated on a cohort-year basis. *Dum1970s, Dum1980s, Dum1990s*, and *Dum2000s* are dummy variables equal to one if the cohort-year observations are for the 1970s, 1980s, 1990s, and 2000s cohort, respectively, and zero otherwise. The dummy variable for pre-1970s banks is considered the reference category and, therefore, is excluded. ε is the error term. All coefficients are multiplied by 100 (except coefficient on ***Year***, called time trend, is multiplied by 1,000). All variables are defined in Appendices 1 and 2. The superscripts a, b, and c indicate significance at a *p*-level of 0.01, 0.05, and 0.10, respectively. *Opposite* in *F*-test indicates that the difference in coefficients is opposite to expectation. Panel A presents results for credit risk; Panel B, for liquidity risk.

Table 4 continued

Time series and cohort trend in bank risks, after controlling for operating characteristics

Panel A: *Credit Risk*											
Variable	Time trend and cohorts	Time trend, cohorts, and *BDGTA*	Difference in cohorts' coefficients (3) - (2)	Time trend, cohorts, and *CRELGTA*	Difference in cohorts' coefficients (5) - (2)	Time trend, cohorts, and *OBSGTA*	Difference in cohorts' coefficients (7) - (2)	Time trend, cohorts, and *NIIOI*	Difference in cohorts' coefficients (9) - (2)	Time trend, cohorts, and all factors	Difference in cohorts' coefficients (12) - (2)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Year	1.469[a]	- 0.062		-1.562[a]		0.529		2.938[a]		-1.056[a]	
Dum1970s	2.168[a]	1.379[c]	-0.789[b]	-4.282[a]	-6.450[a]	0.246	-1.922[a]	3.845[a]	1.677[a]	-2.352[a]	-4.520[a]
Dum1980s	3.701[a]	1.812[b]	-1.889[a]	-4.416[a]	-8.117[a]	-0.327	-4.028[a]	6.933[a]	3.232[a]	-3.083[a]	-6.784[a]
Dum1990s	8.813[a]	3.192[a]	-5.621[a]	-2.440[a]	-11.253[a]	2.098[b]	-6.715[a]	9.808[a]	0.995[b]	-3.643[a]	-12.456[a]
Dum2000s	8.569[a]	3.913[a]	-4.656[a]	-5.053[a]	-13.622[a]	3.595[a]	-5.218[a]	7.443[a]	-1.126[b]	-4.179[a]	-12.992[a]
BDGTA		169.592[a]								55.340[b]	
CRELGTA				77.530[a]						41.990[a]	
OBSGTA						130.635[b]				92.375[a]	
NIIOI								-72.138[a]		-24.048[b]	
Constant	59.153[a]	61.644[a]		56.458[a]		49.244[a]		63.036[a]		53.375[a]	
Observations	114	114		114		104		114		104	
F-value	34.14[a]	47.69[a]		127.83[a]		58.03[a]		35.93[a]		156.92[a]	
Adjusted R^2	59.45%	71.26%		87.07%		76.86%		64.97%		93.16%	
F-test of difference in coefficients on cohort dummies (*p*-values presented)											
1970s > Pre-1970s ($\gamma_1 > 0$)	0.009	0.052		*Opposite*		0.721		0.000		*Opposite*	
1980s > 1970s ($\gamma_2 > \gamma_1$)	0.064	0.544		*Opposite*		*Opposite*		0.000		*Opposite*	
1990s > 1980s ($\gamma_3 > \gamma_2$)	0.000	0.148		0.001		0.002		0.005		*Opposite*	
2000s > 1990s ($\gamma_4 > \gamma_3$)	*Opposite*	0.483		*Opposite*		0.152		*Opposite*		*Opposite*	

Table 4 continued

Time-series and cohort trend in bank risks, after controlling for operating characteristics

Panel B: *Liquidity Risk*											
Variable	Time trend and cohorts	Time trend, cohorts, and *BDGTA*	Difference in cohorts' coefficients (3) - (2)	Time trend, cohorts, and *CRELGTA*	Difference in cohorts' coefficients (5) - (2)	Time trend, cohorts, and *OBSGTA*	Difference in cohorts' coefficients (7) - (2)	Time trend, cohorts, and *NIIOI*	Difference in cohorts' coefficients (9) - (2)	Time trend, cohorts, and all factors	Difference in cohorts' coefficients (12) - (2)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Year × **1,000**	5.774[a]	6.054[a]		4.361[a]		3.170[a]		2.146[a]		0.649	
Dum1970s	6.722[a]	6.870[a]	0.148	4.730[a]	-1.992[a]	4.832[a]	-1.890[a]	3.784[a]	-2.938[a]	1.772[a]	-4.950[a]
Dum1980s	9.168[a]	10.012[a]	0.844[b]	6.212[a]	-2.956[a]	4.575[a]	-4.593[a]	3.525[a]	-5.643[a]	0.548	-8.620[a]
Dum1990s	11.927[a]	16.170[a]	4.243[a]	7.734[a]	-4.193[a]	5.471[a]	-6.456[a]	10.314[a]	-1.613[a]	5.345[a]	-6.582[a]
Dum2000s	13.507[a]	17.455[a]	3.948[a]	8.485[a]	-5.022[a]	9.763[a]	-3.744[a]	15.926[a]	2.419[a]	9.695[a]	-3.812[a]
BDGTA		-132.776[a]								-61.645[a]	
CRELGTA				30.651[a]						35.481[a]	
OBSGTA						117.167[b]				50.001[a]	
NIIOI								115.430[a]		77.238[a]	
Constant	1.680[a]	3.013[a]		1.099		-0.006		-0.102		-0.458	
Observations	144	144		144		134		144		134	
F-value	209.68[a]	244.58[a]		189.90[a]		349.34[a]		366.79[a]		462.02[a]	
Adjusted R^2	87.95%	91.09%		88.80%		94.02%		93.88%		96.89%	
F-test of difference in coefficients on cohort dummies (*p*-values presented)											
1970s > Pre-1970s ($\gamma_1 > 0$)	0.000	0.000		0.000		0.000		0.000		0.003	
1980s > 1970s ($\gamma_2 > \gamma_1$)	0.006	0.000		0.097		*Opposite*		*Opposite*		*Opposite*	
1990s > 1980s ($\gamma_3 > \gamma_2$)	0.009	0.000		0.155		0.253		0.000		0.000	
2000s > 1990s ($\gamma_4 > \gamma_3$)	0.256	0.283		0.581		0.000		0.000		0.000	

Table 5

Cohort-wise sample description across bank size categories

We consider banks in the bottom 25 percentile of gross total assets (GTA) as small banks, those in the top 25 percentile as large banks, and the rest as medium banks. Banks are further sorted into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as a cohort from the 1970s, 1980s, 1990s, or 2000s based on the decade of their opening year. This table reports the annual number of observations by cohorts and size. CADR is compound annual decline rate.

Year	Small banks						Medium banks						Large banks					
	All	Pre-1970s	1970s cohort	1980s cohort	1990s cohort	2000s cohort	All	Pre-1970s	1970s cohort	1980s cohort	1990s cohort	2000s cohort	All	Pre-1970s	1970s cohort	1980s cohort	1990s cohort	2000s cohort
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
1976	2,779	2,779					5,556	5,556					2,778	2,778				
1977	2,779	2,779					5,557	5,557					2,778	2,778				
1978	2,776	2,776					5,552	5,552					2,775	2,775				
1979	2,776	2,776					5,552	5,552					2,775	2,775				
1980	3,172	2,510	662				6,343	5,552	791				3,171	3,039	132			
1981	3,172	2,556	616				6,344	5,529	815				3,172	3,017	155			
1982	3,173	2,597	576				6,342	5,506	836				3,171	2,993	178			
1983	3,168	2,642	526				6,335	5,474	861				3,167	2,969	198			
1984	3,060	2,587	473				6,118	5,268	850				3,059	2,843	216			
1985	2,996	2,556	440				5,990	5,174	816				2,995	2,772	223			
1986	2,910	2,511	399				5,820	5,033	787				2,910	2,688	222			
1987	2,796	2,432	364				5,589	4,867	722				2,794	2,594	200			
1988	2,652	2,329	323				5,304	4,666	638				2,651	2,444	207			
1989	2,555	2,268	287				5,110	4,510	600				2,554	2,337	217			
1990	2,918	2,061	242	615			5,836	4,329	560	947			2,918	2,444	241	233		
1991	2,814	2,048	244	522			5,628	4,168	512	948			2,813	2,344	233	236		
1992	2,731	2,051	227	453			5,461	4,038	478	945			2,730	2,272	230	228		
1993	2,638	2,047	203	388			5,271	3,924	454	893			2,636	2,183	221	232		
1994	2,522	1,995	187	340			5,043	3,763	430	850			2,521	2,077	211	233		
1995	2,381	1,931	166	284			4,762	3,582	399	781			2,380	1,924	197	259		
1996	2,250	1,868	146	236			4,498	3,408	369	721			2,249	1,811	187	251		
1997	2,115	1,799	124	192			4,228	3,227	341	660			2,114	1,665	181	268		
1998	1,986	1,712	108	166			3,971	3,081	314	576			1,985	1,545	176	264		
1999	1,889	1,635	99	155			3,778	2,985	292	501			1,889	1,467	163	259		
2000	2,045	1,529	90	133	293		4,090	2,795	255	441	599		2,044	1,452	177	263	152	
2001	1,960	1,531	90	121	218		3,918	2,677	234	404	603		1,959	1,368	169	252	170	

2002	1,892	1,518	92	116	166		3,782	2,602	212	375	593		1,891	1,309	162	239	181	
2003	1,840	1,506	91	113	130		3,680	2,570	201	341	568		1,840	1,247	162	240	191	
2004	1,774	1,489	87	93	105		3,548	2,521	192	314	521		1,774	1,180	150	228	216	
2005	1,708	1,463	85	80	80		3,416	2,458	176	309	473		1,708	1,099	150	220	239	
2006	1,639	1,411	80	79	69		3,278	2,399	165	289	425		1,638	1,067	142	201	228	
2007	1,576	1,371	71	73	61		3,152	2,331	168	262	391		1,575	1,019	132	200	224	
2008	1,515	1,314	72	72	57		3,030	2,280	156	236	358		1,514	981	128	192	213	
2009	1,465	1,269	70	74	52		2,929	2,226	149	227	327		1,464	967	125	168	204	
2010	1,658	1,266	67	68	57	200	3,315	2,054	140	201	267	653	1,657	1,032	114	155	203	153
2011	1,610	1,239	65	68	57	181	3,220	2,033	132	192	252	611	1,610	1,012	108	142	188	160
2012	1,698	1,304	71	69	60	194	3,395	2,232	136	206	255	566	1,697	1,073	105	154	183	182
2013	1,632	1,276	69	68	56	163	3,263	2,180	127	191	234	531	1,631	1,028	98	147	175	183
2014	1,560	1,236	69	61	51	143	3,118	2,105	119	185	225	484	1,559	989	95	135	154	186
2015	1,483	1,188	69	59	43	124	2,965	2,046	111	168	206	434	1,482	943	87	128	143	181
2016	1,419	1,140	67	58	46	108	2,838	1,999	108	155	186	390	1,419	898	84	117	136	184
2017	1,361	1,098	62	59	47	95	2,722	1,954	107	148	159	354	1,360	857	76	111	133	183
2018	1,297	1,059	63	56	42	77	2,592	1,873	103	145	144	327	1,296	824	74	106	126	166
2019	1,238	1,029	58	55	36	60	2,476	1,809	92	139	136	300	1,238	789	70	99	120	160
CADR (%)		-2.28	-6.05	-7.99	-10.45	-12.52		-2.58	-5.37	-6.40	-7.51	-8.28		-2.88	-1.61	-2.91	-1.24	0.50

Table 6

Time series and cohort trend in bank risks, by size categories

We consider banks in the bottom 25 percentile of gross total assets (GTA) as small banks, those in the top 25 percentile as large banks, and the rest as medium banks. Banks are further sorted into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as a cohort from the 1970s, 1980s, 1990s, or 2000s based on the decade of their opening year. Each observation is a cohort-year average, yielding a sample that contains 144 cohort-year observations: 44 annual observations for the pre-1970 banks (1976 to 2019), 40 annual observations for the 1970s cohort (1980 to 2019), 30 annual observations for the 1980s cohort (1990 to 2019), 20 annual observations for the 1990s cohort (2000 to 2019), and ten annual observations for the 2000s cohort (2010 to 2019). For credit risk, we use 114 cohort-year observations (28 annual observations for the pre-1970 banks, 1970s cohort, and 1980s cohort). We estimate the regression by size category:

$$Risk_{cohort,\,year} = \beta_0 + \beta_1 \times Year + \gamma_1\, Dum1970s + \gamma_1\, Dum1980s + \gamma_2\, Dum1990s + \gamma_3\, Dum2000s + \varepsilon_{cohort,\,year},$$

where *Risk* is the liquidity risk (or credit risk) calculated on a cohort-year basis. *Dum1970s, Dum1980s, Dum1990s*, and *Dum2000s* are dummy variables equal to one if the cohort-year observations are for the 1970s, 1980s, 1990s, and 2000s cohort, respectively, and zero otherwise. The dummy variable for pre-1970s banks is considered the reference category and, therefore, is excluded. ε is the error term. All coefficients are multiplied by 100 (except coefficient on *Year*, called time trend, is multiplied by 1,000). All variables are defined in Appendices 1 and 2. The superscripts a, b, and c indicate significance at a *p*-level of 0.01, 0.05, and 0.10, respectively. *Opposite* in *F*-test indicates that the difference in coefficients is opposite to expectation. Panel A presents results for credit risk; Panel B, for liquidity risk.

Panel A: Credit Risk								
Variable	Time trend				Time trend and cohorts			
	All	Small	Medium	Large	All	Small	Medium	Large
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year × **1,000**	2.653[a]	0.999[b]	2.743[a]	3.219[a]	1.469[a]	-0.406[a]	1.559[a]	2.441[a]
Dum1970s					2.168[a]	-1.310[a]	2.168[b]	2.782[a]
Dum1980s					3.701[a]	2.100[a]	3.637[a]	2.409[b]
Dum1990s					8.813[a]	6.159[a]	8.479[a]	7.366[a]
Dum2000s					8.569[a]	9.625[a]	8.763[a]	5.325[a]
Constant	59.108[a]	59.198[a]	58.695[a]	60.857[a]	59.153[a]	61.576[a]	58.801[a]	60.311[a]
Observations	114	114	114	114	114	114	114	114
F-value	26.31[a]	4.19[b]	27.17[a]	42.43[a]	34.14[a]	39.88[a]	30.24[a]	23.33[a]
Adjusted R^2	18.30%	2.75%	18.81%	26.83%	59.45%	63.24%	56.40%	49.70%
F-test of difference in coefficients on cohort dummies (*p*-values presented)								
1970s > Pre-1970s ($\gamma_1 > 0$)					0.009	*Opposite*	0.014	0.003
1980s > 1970s ($\gamma_2 > \gamma_1$)					0.064	0.000	0.094	*Opposite*
1990s > 1980s ($\gamma_3 > \gamma_2$)					0.000	0.000	0.000	0.000
2000s > 1990s ($\gamma_4 > \gamma_3$)					*Opposite*	0.001	0.824	*Opposite*
Panel B: Liquidity Risk								
Time trend × **1,000**	7.402[a]	5.560[a]	7.415[a]	7.820[a]	5.774[a]	3.738[a]	5.689[a]	7.037[a]
Dum1970s					6.722[a]	3.719[a]	7.458[a]	5.860[a]
Dum1980s					9.168[a]	8.458[a]	9.749[a]	5.604[a]
Dum1990s					11.927[a]	10.331[a]	12.570[a]	6.621[a]
Dum2000s					13.507[a]	16.037[a]	14.699[a]	7.303[a]
Constant	3.597[a]	1.125[a]	3.254[a]	8.506[a]	1.680[a]	0.768	1.107[a]	6.426[a]
Observations	144	144	144	144	144	144	144	144
F-value	344.51[a]	193.80[a]	298.08[a]	500.57[a]	209.68[a]	136.44[a]	183.29[a]	153.07[a]
Adjusted R^2	70.61%	57.41%	67.51%	77.75%	87.95%	82.57%	86.44%	84.17%
F-test of difference in coefficients on cohort dummies (*p*-values presented)								
1970s > Pre-1970s ($\gamma_1 > 0$)					0.000	0.000	0.000	0.000
1980s > 1970s ($\gamma_2 > \gamma_1$)					0.006	0.000	0.016	*Opposite*
1990s > 1980s ($\gamma_3 > \gamma_2$)					0.000	0.073	0.014	0.397
2000s > 1990s ($\gamma_4 > \gamma_3$)					0.256	0.000	0.159	0.671

Table 7

Time series and cohort trend in bank risks, by bank size, after controlling for operating characteristics

We consider banks in the bottom 25 percentile of gross total assets (GTA) as small banks, those in the top 25 percentile as large banks, and the rest as medium banks. Banks are further sorted into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as a cohort from the 1970s, 1980s, 1990s, or 2000s based on the decade of their opening year. Each observation is a cohort-year average, yielding a sample that contains 144 cohort–year observations: 44 annual observations for the pre-1970 banks (1976 to 2019), 40 annual observations for the 1970s cohort (1980 to 2019), 30 annual observations for the 1980s cohort (1990 to 2019), 20 annual observations for the 1990s cohort (2000 to 2019), and ten annual observations for the 2000s cohort (2010 to 2019). For credit risk, we use 114 cohort–year observations (28 annual observations for the pre-1970 banks, 1970s cohort, and 1980s cohort). We estimate the regression by size category:

$$Risk_{cohort,\, year} = \beta_0 + \beta_1 \times Year + \beta_2 \times Characteristic_{cohort;\, year} + \gamma_1\, Dum1970s + \gamma_1\, Dum1980s + \gamma_2\, Dum1990s + \gamma_3\, Dum2000s + \varepsilon_{cohort,\, year},$$

where ***Risk*** is the liquidity risk (or credit risk) calculated on a cohort-year basis. Characteristic refers to the average of one of the bank-specific factors (brokered deposits, commercial real estate loans, off–balance sheet items, or noninterest income) calculated on a cohort-year basis. *Dum1970s*, *Dum1980s*, *Dum1990s*, and *Dum2000s* are dummy variables equal to one if the cohort-year observations are for the 1970s, 1980s, 1990s, and 2000s cohort, respectively, and zero otherwise. The dummy variable for pre-1970s banks is considered the reference category and, therefore, is excluded. ε is the error term. All coefficients are multiplied by 100 (except coefficient on *Year*, called time trend, is multiplied by 1,000). All variables are defined in Appendices 1 and 2. The superscripts a, b, and c indicate significance at a *p*-level of 0.01, 0.05, and 0.10, respectively. *Opposite* in ***F***-test indicates that the difference in coefficients is opposite to expectation. Panel A presents results for credit risk; Panel B, for liquidity risk.

Panel A: *Credit Risk*															
	Control for *BDGTA*			Control for *CRELGTA*			Control for *OBSGTA*			Control for *NIIOI*			All factors		
Variable	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Year × **1,000**	-1.026[a]	0.204	0.969[a]	-2.591[a]	-1.706[a]	-0.868[a]	-0.293	1.102[a]	1.575[a]	-0.263	3.031[a]	3.656[a]	-1.615[a]	-0.603	-2.536[a]
Dum1970s	-0.937	1.814[b]	1.809[a]	-5.370[a]	-4.699[a]	-1.819[a]	-0.281	0.251	2.346[a]	-0.837	4.079[a]	2.802[a]	-2.517[a]	-1.968[a]	-1.153[a]
Dum1980s	2.059[a]	2.463[a]	0.086	-6.090[a]	-5.628[a]	-0.864[a]	0.851	0.441	-0.371	3.185[a]	6.329[a]	3.975[a]	-2.906[a]	-2.701[a]	-4.405[a]
Dum1990s	4.569[a]	3.514[a]	1.908	-8.067[a]	-4.252[a]	3.302[a]	0.643	2.444[b]	3.674[a]	7.199[a]	8.532[a]	7.532[a]	-7.236[a]	-4.522[a]	-2.281[b]
Dum2000s	7.643[a]	3.862[a]	-0.031	-12.973[a]	-6.869[a]	1.616[a]	5.514[a]	3.106[b]	1.322	9.998[a]	7.500[a]	3.491[b]	-10.521[a]	-5.763[a]	-3.233[a]
BDGTA	165.009[a]	197.684[a]	111.025[a]										5.869	86.290[a]	68.374[a]
CRELGTA				98.534[a]	83.668[a]	58.202[a]							72.669[a]	41.089[a]	42.027[a]
OBSGTA							149.387[a]	134.005[a]	96.484[b]				126.246[a]	99.018[a]	82.019[a]
NIIOI										-18.246	-68.057[a]	-50.684[a]	-32.451[b]	-28.140[a]	18.196[b]
Constant	62.159[a]	60.714[a]	62.457[a]	59.783[a]	55.498[a]	57.204[a]	51.802[a]	48.714[a]	47.192[a]	62.869[a]	61.819[a]	64.343[a]	54.083[a]	52.467[a]	48.189[a]
Observations	114	114	114	114	114	114	104	104	104	114	114	114	104	104	104
F-value	36.25[a]	43.06[a]	30.22[a]	57.67[a]	129.44[a]	63.21[a]	66.45[a]	54.91[a]	34.92[a]	33.94[a]	30.02[a]	23.92[a]	78.01[a]	181.04[a]	104.25
Adjusted R^2	65.18%	69.07%	60.81%	75.05%	87.21%	76.76%	79.22%	75.85%	66.40%	63.62%	60.64%	54.90%	87.06%	94.02%	90.02%
F-test of difference in coefficients on cohort dummies (*p*-values presented)															
1970s > Pre-1970s ($\gamma_1 > 0$)	*Opposite*	0.015	0.032	*Opposite*	*Opposite*	*Opposite*	*Opposite*	0.724	0.003	*Opposite*	0.000	0.002	*Opposite*	*Opposite*	*Opposite*
1980s > 1970s ($\gamma_2 > \gamma_1$)	0.000	0.383	*Opposite*	*Opposite*	*Opposite*	0.138	0.047	0.786	*Opposite*	0.000	0.009	0.229	*Opposite*	*Opposite*	*Opposite*
1990s > 1980s ($\gamma_3 > \gamma_2$)	0.009	0.291	0.089	*Opposite*	0.016	0.000	*Opposite*	0.016	0.000	0.000	0.065	0.001	*Opposite*	*Opposite*	0.001
2000s > 1990s ($\gamma_4 > \gamma_3$)	0.002	0.746	*Opposite*	*Opposite*	*Opposite*	*Opposite*	0.000	0.532	*Opposite*	0.012	*Opposite*	*Opposite*	*Opposite*	*Opposite*	*Opposite*

Table 7 continued

Time series and cohort trend in bank risks, by bank size, after controlling for operating characteristics

Panel B: *Liquidity Risk*

	Control for *BDGTA*			Control for *CRELGTA*			Control for *OBSGTA*			Control for *NIIOI*			All factors		
Variable	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
(1)	(2)	(3)	(4)	(5)	(14)	(15)	(16)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Year × **1,000**	3.057^{a}	5.909^{a}	7.761^{a}	2.258^{a}	3.695^{a}	6.198^{a}	2.156^{a}	3.330^{a}	3.923^{a}	1.663^{a}	2.019^{a}	3.299^{a}	0.241	0.555	1.025
Dum1970s	2.828^{a}	7.421^{a}	6.472^{a}	1.332^{a}	4.624^{a}	5.036^{a}	3.686^{a}	5.130^{a}	4.584^{a}	0.813	3.988^{a}	5.278^{a}	-0.027	1.958^{a}	3.192^{a}
Dum1980s	7.748^{a}	10.130^{a}	7.613^{a}	3.367^{a}	5.272^{a}	4.968^{a}	5.721^{a}	5.315^{a}	1.079	2.138^{b}	4.738^{a}	1.727^{a}	-0.504	1.199	-0.171
Dum1990s	11.879^{a}	15.945^{a}	12.431^{a}	1.368^{a}	6.388^{a}	5.800^{a}	4.373^{a}	6.106^{a}	2.072^{b}	4.686^{a}	12.500^{a}	6.036^{a}	-1.367	5.835^{a}	3.760^{a}
Dum2000s	18.652^{a}	18.388^{a}	13.443^{a}	1.795^{a}	7.215^{a}	6.604^{a}	12.379^{a}	9.908^{a}	4.074^{a}	14.611^{a}	17.466^{a}	11.207^{a}	4.315	10.021^{a}	8.665^{a}
BDGTA	-170.624^{a}	-136.916^{a}	-120.953^{a}										-91.349^{a}	-45.193^{c}	-41.261^{b}
CRELGTA				62.659^{a}	42.416^{a}	13.337							46.658^{a}	29.237^{a}	29.254^{a}
OBSGTA							138.990^{a}	130.461^{a}	97.247^{a}				73.282^{a}	75.954^{a}	56.483^{b}
NIIOI										97.441^{a}	117.323^{a}	95.372^{a}	51.088^{a}	75.271^{a}	63.280^{a}
Constant	4.816^{a}	2.325^{a}	7.257^{a}	-0.144^{a}	0.330^{a}	5.881^{a}	-1.602^{b}	-1.312^{b}	1.697^{b}	-1.548^{b}	-0.209	4.114^{a}	-0.030	-1.118^{b}	1.435^{b}
Observations	144	144	144	144	144	144	134	134	134	144	144	144	134	134	134
F-value	214.58^{a}	187.09^{a}	176.22^{a}	121.26^{a}	176.02^{a}	129.37^{a}	189.33^{a}	343.45^{a}	294.52^{a}	234.24^{a}	264.64^{a}	229.57^{a}	279.55^{a}	358.20^{a}	290.87^{a}
Adjusted R^2	89.96%	88.65%	88.03%	83.46%	88.01%	84.34%	89.47%	93.92%	92.98%	90.73%	91.71%	90.56%	94.96%	96.03%	95.15%
F-test of difference in coefficients on cohort dummies (*p*-values presented)															
1970s > Pre-1970s ($\gamma_1 > 0$)	0.000	0.000	0.000	0.236	0.000	0.000	0.000	0.000	0.000	0.197	0.000	0.000	*Opposite*	0.007	0.000
1980s > 1970s ($\gamma_2 > \gamma_1$)	0.000	0.002	0.206	0.108	0.503	*Opposite*	0.007	0.788	*Opposite*	0.063	0.324	*Opposite*	*Opposite*	*Opposite*	*Opposite*
1990s > 1980s ($\gamma_3 > \gamma_2$)	0.000	0.000	0.000	*Opposite*	0.325	0.488	*Opposite*	0.330	0.236	0.001	0.000	0.000	*Opposite*	0.000	0.000
2000s > 1990s ($\gamma_4 > \gamma_3$)	0.000	0.079	0.468	0.850	0.568	0.615	0.000	0.001	0.091	0.000	0.000	0.000	0.000	0.000	0.000

Appendix 1

Description of variables

Variable	Description
GTA	Gross total assets = total assets + allowance for loan and lease losses + allocated transfer risk reserve (a reserve for certain foreign loans).
Profitability	Return on equity (ROE) is net income divided by total equity.
Growth	Growth rate of gross total assets.
Credit Risk	Risk-weighted assets and off–balance sheet activities divided by GTA. A higher value indicates higher riskiness.
Liquidity Risk	Liquidity risk measure (as proposed by Berger and Bouwman, 2009) represents a bank's liquidity creation, which considers several on– and off–balance sheet items shown in Appendix 2. It measures to what degree a bank can finance illiquid assets with liquid liabilities. It is scaled by GTA. A high value indicates high liquidity risk.
BDGTA	Brokered deposits divided by GTA.
CRELGTA	Commercial real estate loans (construction and land development loans + real estate loans secured by multi-family (five or more) residential properties + real estate loans secured by nonfarm nonresidential properties) divided by GTA.
OBSGTA	Off–balance sheet (unused commitments + derivatives) divided by GTA.
NIIOI	Noninterest income divided by total operating income (interest income + noninterest income).
Dum1970s	Dummy variable equals one if the bank opened between 1970 and 1979.
Dum1980s	Dummy variable equals one if the bank opened between 1980 and 1989.
Dum1990s	Dummy variable equals one if the bank opened between 1990 and 1999.
Dum2000s	Dummy variable equals one if the bank opened between 2000 and 2019.

Appendix 2

Methodology to construct liquidity risk measure

This table explains Berger and Bouwman (2009) methodology to construct liquidity risk measure in three steps:
Step 1: Bank activities are classified as liquid and illiquid, based on the bank activities category in Panel A.
Step 2: Weights are assigned to all bank activities classified in Step 1.

Panel A: Liquidity classification of bank activities	
Assets	
Illiquid assets (weight = ½)	Liquid assets (weight = -½)
Commercial real estate loans (CRE) Loans to finance agricultural production Commercial and industrial loans (CandI) Other loans and lease financing receivables Other real estate owned (OREO) Investment in unconsolidated subsidiaries Customers' liability on bankers' acceptances Intangible assets Premises Other assets	Cash and due from other institutions All securities (regardless of maturity) Trading assets Fed funds sold
Liabilities and equity	
Liquid liabilities (weight = ½)	Illiquid liabilities + equity (weight = -½)
Transactions deposits Savings deposits Overnight federal funds purchased trading Trading liabilities	Bank's liability on bankers' acceptances Subordinated debt Other liabilities
Off–balance sheet	
Illiquid guarantees (weight = ½)	Liquid guarantees and derivatives (weight = -½)
Unused commitment Net standby letters of credit Commercial and similar letters of credit All other off–balance sheet liabilities	Net participations acquired Interest rate derivatives Foreign exchange derivatives Equity and commodity derivatives
Panel B: Calculation of liquidity creation measure	
Liquidity Risk = [(1/2 × illiquid assets + 1/2 × liquid liabilities + 1/2 × illiquid guarantees) – (1/2 × liquid assets + 1/2 × illiquid liabilities + 1/2 × liquid guarantees and derivatives)]	

Step 3: The bank activities classification in Step 1 is combined with weights in Step 2 in two ways to construct the liquidity creation measure (*cat fat*) shown in Panel B.