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Schumpeterian creative destruction and temporal changes in business models of US banks

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ABSTRACT

Schumpeter theorizes that capitalism is characterized by a constant process of creative destruction. Newcomers introduce disruptive innovations and technologies that replace older, less efficient business practices. Thus, established firms must either continually adapt or perish. Christensen (1997) argues that large, established firms cannot innovate as fast as newcomers and thus are likely to perish over time. We test these predictions in the setting of the United States banking sector. We examine banks' credit and liquidity risks as proxies for their business models, as well as their reliance on brokered deposits, commercial real estate loans, off-balance sheet items, and noninterest income as proxies for operational strategies. We find that banks' credit and liquidity risks increased significantly over the last 40 years or so, indicating a steady change in banks' business models. This trend stems primarily from progressively aggressive business models introduced by incoming cohorts. Older cohorts respond to changing market conditions by increasing the aggressiveness of their own business models, but not as much as the newcomers. Surprisingly, surviving large banks among older cohorts change their business models faster than smaller banks from the same cohorts. Thus, while we find support for Schumpeterian creative destruction and Christensen's (1997) arguments, we also find that large and established banks are better able to adapt to new market conditions, perhaps because they have superior access to resources and talent necessary to implement transformation. Our findings at least partly explain why the dominant players in the US banking sector have remained the same decade after decade.

1. Introduction

Schumpeterian creative destruction (Schumpeter, 1942) and Christensen's (1997) notion of disruptive innovation are two prominent theories that describe the dynamic process of innovation and economic change in a capitalist system. According to economist Joseph Schumpeter, capitalism is characterized by a constant process of creative destruction. New firms introduce innovative products, processes, and business models that disrupt existing industries and markets. Established firms and industries that fail to adapt to new practices diminish or go extinct over time. Christensen's (1997) theory of disruptive innovation describes that large, successful organizations struggle to respond effectively to disruptive technologies or business models. He offers five reasons for their lack of change: focus on sustaining current profits at the cost of neglecting disruptive innovations, overconfidence in the current business model, aversion to risk-taking, narrow focus on existing operations, and inertia that comes from deep-rooted, rigid organizational structures. Stated differently, both Schumpeter and renowned management theorist Clayton Christensen predict that newcomers will introduce new ways of doing business and that organizations that keep up with new business models would more likely survive and grow than organizations with static business models. We test these predictions in the setting of the US banking sector.

The banking industry has always been an integral part of the US economy. Although it has gone through multiple changes over the last 40 years or so [for example, deregulation and institutional changes, implementation of new capital requirements, financial innovations in off-balance sheet items, integration of markets, and technological advancements (see Rajan, 2006)], we assume that all US banks are subject to similar regulation and economic shocks over time. We test changes in banks' business models by turning just one dial, banks' formation years. We focus only on the US banking sector, thereby ignoring other banks

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around the world, as they would be subject to different, regional economic shocks and regulations, creating confounds that are difficult to control in our empirical tests.

We examine changes in banks' business models by focusing on changes in their liquidity and credit risks, the two principal factors in bank failure (Imbierowicz & 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 & Bouwman, 2009; Berger, Bouwman, Kick, & Schaeck, 2016; and Khan, Scheule, & Wu, 2017). We also examine operational strategies that contribute to these 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 document four stylized facts. The first fact, as illustrated in Fig. 1, is that the 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 2007–2009 global financial crisis (GFC), its rising trend resumed thereafter. The brief period of more prudent lending after the GFC was just an intermittent response to the financial crisis. Overall, the rising trend in the two risk measures suggests a secular change in banks' business practices, at least when observed as cross-sectional averages over time. These trends provide preliminary evidence of the evolution of banks' business models.

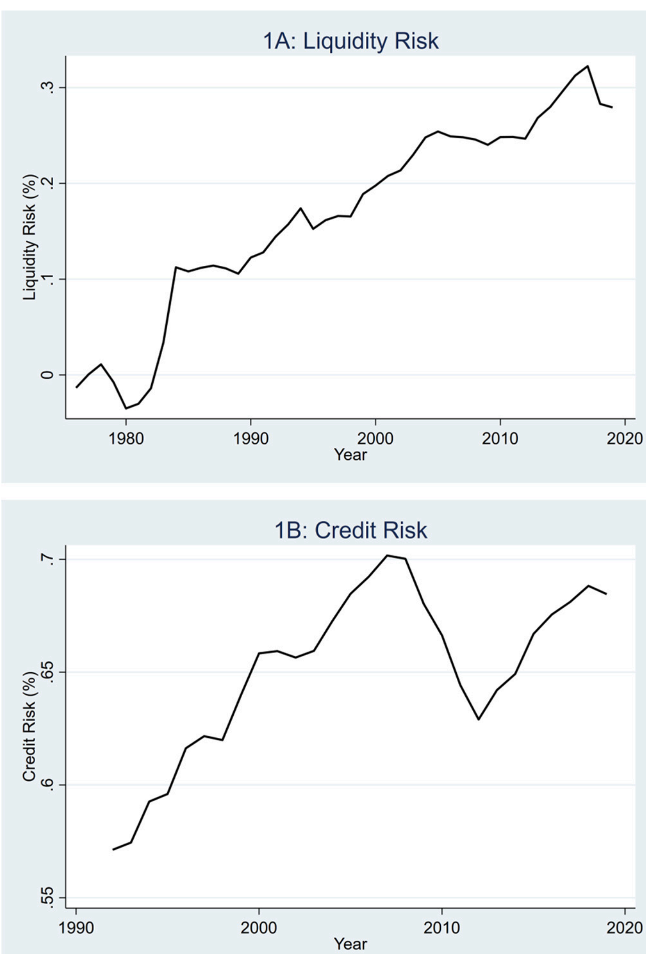

Fig. 1. Time series trend in banks' liquidity and credit risks.
This figure illustrates the annual averages of liquidity risk (1 A) and credit risk (1B) for US banks. All variables are defined in Appendices 1 and 2.

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, which illustrates changing business models introduced by newer cohorts over time. One plausible explanation for the cohort risk phenomenon is that given saturation in traditional segments, new players keep searching for alternative avenues to fuel growth, and to avoid monitoring cost and capital adequacy requirements. This stylized fact supports Schumpeter's argument that newcomers introduce innovative products, processes, and business models.

Notably, risks of all cohorts rise with time, indicating that even legacy banks increase the aggressiveness of their operating strategies, which, in combination with the riskier strategies of newcomers, increases the overall risk in the banking sector. Results are consistent with Schumpeter's argument that established firms must innovate to survive. Nevertheless, these results may seem inconsistent with Christensen (1997), who would expect that older cohorts, suffering from overconfidence, inertia, or higher risk aversion, would be unable to innovate. Yet, the consistent inter-cohort differences indicate that older cohorts are unable to completely change their business models to catch up with innovations introduced by newer cohorts. This is consistent with Christensen's (1997) theory that older, successful organizations are unable to keep pace with newcomers.

The third fact comes from dividing our sample into small, medium, and large banks. Fig. 3 shows that the rising trend observed in Fig. 1 prevails across all size categories. That is, regardless of their size, banks have increased the aggressiveness of their operating strategies over time, on average.

The fourth fact, and our main contribution comes from examining the cohort risk phenomenon within each size category. The findings about the cohort risk phenomenon remain qualitatively unchanged. That is, we find both time trends of increase in overall risks and persistent inter-cohort differences across all three size categories. Figs. 4 and 5 surprisingly show the strongest time trends, but the smallest inter-cohort differences, for large banks. In contrast, the time trend is lowest for small banks, and the inter-cohort differences are the largest.

These contrasting results for large and small banks indicate two things: The business models of large banks are changing at a faster rate than for small banks, and the divergence between old cohorts and new cohorts is occurring at the lowest rate for large 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.[1] The result indicates that larger banks among old cohorts are more dynamic in adopting newer operating strategies than their smaller counterparts. This might appear counterintuitive and contrary to the disruptive innovation idea of Christensen (1997), who would expect higher inertia among larger banks. Yet, results are consistent with Gerstner (2003), the erstwhile chief executive officer of

[1] Results support Delis et al. (2014), who find that, after 2004, the risk measures of large banks surpassed the industry average, consistent with the idea that larger banks innovated faster than smaller banks in the brief period after 2014.

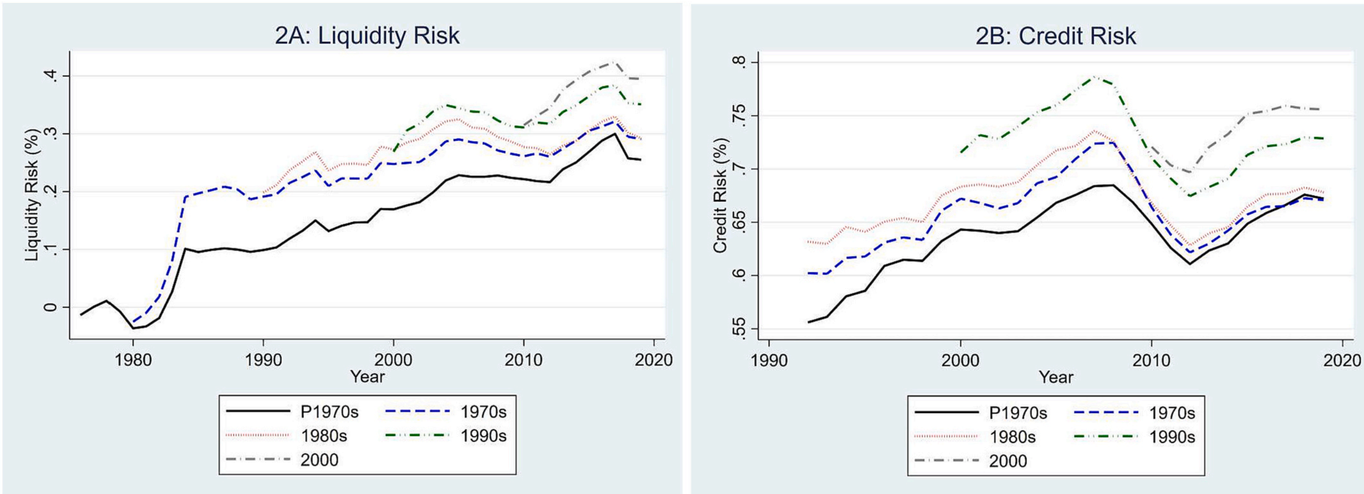

Fig. 2. Cohort trends in banks' credit and liquidity risks.
This figure shows cohort trends of liquidity risk (2 A) and credit risk (2B) for US banks. The banks are sorted into five cohorts based on their year of opening. All banks with an opening year before 1970 are classified as pre-1970 banks. The 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.

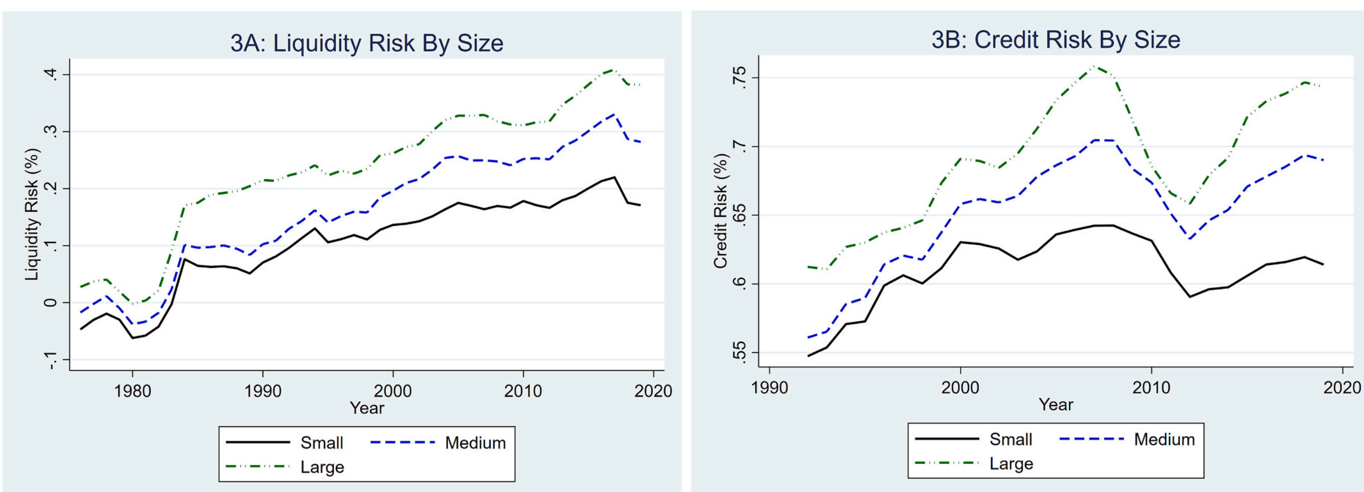

Fig. 3. Time series trends in banks' liquidity and credit risks by size categories.
We consider banks in the bottom 25 percentile of gross total assets (GTA) as small banks, those in the top 25 percentile as large banks, and the rest as medium banks. This figure illustrates the annual averages of liquidity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

IBM, who said: "Who says elephants can't dance?" At least a few large established banks plausibly could change faster than small banks, given large banks' resources to change and economic size and capacity to adopt to riskier business strategies in line with the overall market.[2] Another credible explanation is that only those large banks that innovate, prosper, and can maintain market share survive, while those that do not innovate diminish over time (that is, they are no longer in the large-size sample). Our findings based on ex-post observations are consistent with both explanations.

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 global financial crisis], and by limiting the sample to true commercial banks. We continue to find significant cohort patterns and support for our predictions.

In summary, we demonstrate a steady pace of Schumpeterian innovation in the US banking sector over the last 40 years or so, arguably because of riskier business models introduced by the newcomers. Consistent with Christensen (1997), we find that older cohorts change their business models to survive but are unable to completely change their business models to keep pace with incoming cohorts. Contrary to Christensen (1997), we find that larger banks among older cohorts change faster than the smaller banks from the same cohorts, maintaining their dominant positions in the market.

Our findings should interest researchers, regulators, and policymakers, as we examine theories of organizational changes in an

[2] 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.

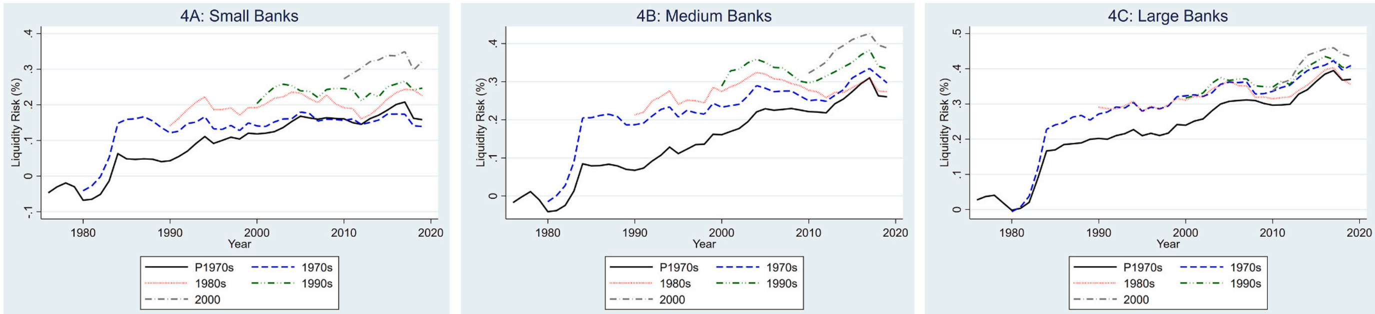

Fig. 4. Cohort trends in banks' liquidity risk by size categories.
We consider banks in the bottom 25 percentile of gross total assets (GTA) as small banks, those in the top 25 percentile as large banks, and the rest as medium banks. Banks are further sorted into five cohorts based on their year of opening. 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 for small, medium, and large banks on an annual basis. All variables are defined in Appendices 1 and 2.

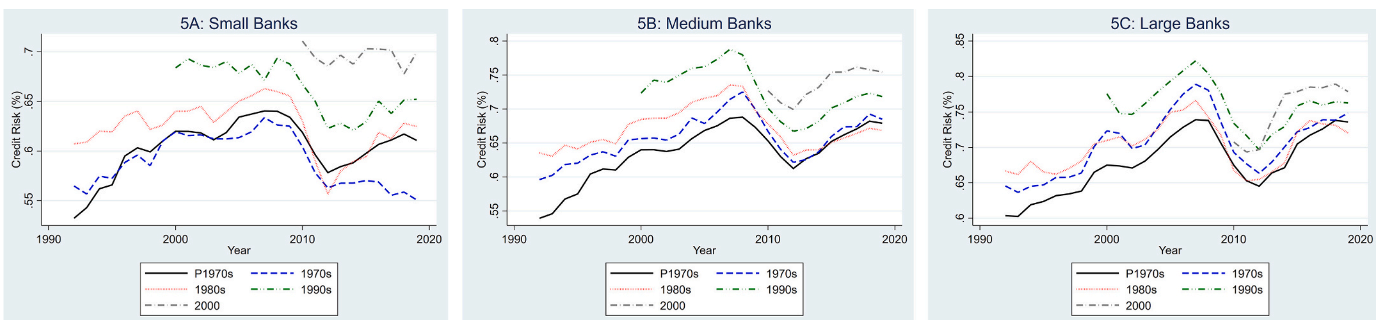

Fig. 5. Cohort trends in banks' credit risk by size categories.
We consider banks in the bottom 25 percentile of gross total assets (GTA) as small banks, those in the top 25 percentile as large banks, and the rest as medium banks. Banks are further sorted into five cohorts based on their year of opening. 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 credit risk for small, medium, and large banks on an annual basis. All variables are defined in Appendices 1 and 2.

important sector of the economy. Our research question is meritorious for two reasons. First, the large established banks of today are the same as they were a decade ago, a decade before that, and all the way to before the 1970s. This is a pattern that merits investigation, especially because it does not hold for other capital-intensive service sectors, such as telecommunications (disrupted by innovators such as Zoom, Teams, and WhatsApp) and hotels (disrupted by AirBnB). Despite all the talk about fintechs and new technologies disrupting the banking sector, the market leaders in the banking sector remain largely the same as 50 years ago. Newcomers must resort to riskier and riskier business models to gain any market share. This stylized fact must interest banking regulators and policymakers, as banking is a highly regulated sector but is important to the economy. The welfare implications of this change or lack of change are left to future studies.

Second, the proxies of business models we examine, credit and liquidity risks, should be of interest to regulators as those risks are strongly and independently associated with probabilities of bank default and failure (Imbierowicz & Rauch, 2014).[3] Past 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 global financial crisis was its "funding framework" and "balance sheet management."[4] Recent bank failures such as Silicon Valley Bank point to factors such as asset-liability mismatch and liquidity risk. Banks' business models and associated risks play a significant role in maintaining the resilience and stability of the banking system and, consequently, the wider economy. Our paper contributes to a better understanding of how those factors evolve. Our study also points to riskier policies being adopted by newcomers, arguably given the control over the market held by large, established players.

We make this point by demonstrating the downside of riskier business strategies of successive cohorts after a black swan event: the global financial crisis, which could have a double-whammy impact. On one side, larger credit risks would imply higher default rates by the client. On the other side, higher liquidity risks would mean that the banks would be unable to meet their short-term obligations. This dual effect could lead to bank failure. As we expect, the pre-1970s, 1970s, 1980s, and 1990s cohorts display a progressively higher attrition rate in the two

[3] The Material Loss Reports of the Federal Deposit Insurance Corporation (FDIC) and the Office of the Comptroller of the Currency (OCC) find liquidity and credit risks to be significant determinants of bank failures. 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.

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

years following the crisis.[5] That is, 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.

2. Related literature

The literature related to the concepts we examine is extensive and diverse. We limit our discussion to prominent ideas and papers that provide theoretical underpinnings for our paper.

2.1. Theories on organizational change over time

Creative destruction is the dynamic process of innovation and economic change in a capitalist system. According to Schumpeter, capitalism is characterized by an ongoing process of change whereby new innovations and technologies replace older, less efficient ones, leading to the transformation and progress of the economy. The impetus for this creative destruction comes from new firms or entrepreneurs introducing innovative products, processes, or business models that disrupt existing industries and markets. Such disruptions could cause decline or even extinction of established firms and industries that fail to adapt or keep up with the changes. While the demise of established firms and industries can lead to unemployment, economic dislocation, and social upheaval, the ongoing process of replacing old technologies and industries with new ones leads to economic growth and progress, albeit with some short-term costs and adjustments.

Christensen developed, and first introduced in his 1997 book *The Innovator's Dilemma*, the theory of disruptive innovation, which shed light on why successful organizations struggle to adapt to changes introduced by newcomers and how they fall victim to disruptive technologies. He identified five reasons that large corporations fail to keep pace with innovations introduced by newcomers. First, successful companies focus on maintaining their market dominance in existing markets and neglect disruptive innovations that initially serve smaller or emerging markets but have the potential to expand to the entire market. Second, successful organizations become complacent and overly confident in their established business models by assuming that their current practices and products will continue to be relevant and successful. Third, successful companies avoid taking risks as they have more to lose by trying unproven technologies instead of maintaining profitability and stability from old technologies. Fourth, focus on appropriating value from existing customers could lead to neglect of new opportunities and markets. Fifth, large organizations often develop rigid structures, processes, and cultures that can hinder their ability to adapt to change. The inertia of an established system can make gaining traction within the company difficult for new ideas or innovations, stifling creativity and inhibiting the exploration of disruptive possibilities.

Christensen's predictions are consistent with 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 can survive far into the future with their founding structures largely intact.

2.2. Changes in US banking regulations over time

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.

Significant regulations affected the US banking sector during our study period. We rely on the Federal Deposit Insurance Corporation (FDIC) to identify these prominent regulations during our study period, instead of scholarly literature.[6] 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 public 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 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. The act 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 counseling. 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

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

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

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.

2.3. Technological trends in banking

Technological developments have impacted many information-based industries, and the banking sector has not been left untouched.[7] 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 (Thakor, 2020). On the other hand, technology has enabled many new nonbanking 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 development 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 (Meta), Google (Alphabet), and Samsung are working towards online payment and digital wallet 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 the population as 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, a more stable funding model, and vaster reach, and they touch multiple aspects of their customer base 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 the technological front cannot be ignored. Banks can no longer so easily attract talented manpower among new graduates who prefer to work for fintechs.

2.4. Differences between large and small banks and the life-cycle effect

Prior studies examine the differences between young and old banks and between small and large banks. DeYoung and Hasan (1998) find that new banks are less 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 show higher variations in profit, suggesting that young banks are riskier than established banks.

DeYoung (1999) finds that, in the first 12 years of their life, 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 of life, and declines thereafter. The study shows that the first six years are the most difficult years in the life of the bank and that the probability of bank failure declines thereafter. DeYoung (2003) finds that new banks and established banks fail for similar operational reasons, but new banks are more sensitive to adverse changes in market conditions. In general, studies conclude that newer banks are riskier and more likely to fail than their established counterparts.

Delis, Hasan, and Tsionas (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 increased. Surprisingly, small, and very small banks became less risky than the average, and the risks of large banks surpassed 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.

3. Hypotheses development

Drawing from the discussion in Section 2, we explain the reasons for our hypothesis.

3.1. 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 show an increase in those risks over time. Berger and Bouwman (2009) report that liquidity creation by US 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 this 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) examine various measures of risk for the US 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 global 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, credit risk resumed its rising trend and reached pre-financial crisis levels.

We thus offer H1.

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

Liquidity and credit risk levels would reflect the aggregate effect of changes in regulation, business models, technologies, and market conditions in the US banking industry. Furthermore, test results for this hypothesis would show the pace of changes in the US banks' business models.

3.2. 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.

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 be revealed by the following question: Is a bank that began its operations in 1970, and must have stabilized its

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

operations by the time it turned seven years old in 1977 (DeYoung, 1999), 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 nonbanking context, Brown and Kapadia (2007), Srivastava (2014), and Srivastava and Tse (2016) find systematic patterns in the business characteristics, firm-specific risks (volatility in stock return that cannot be explained by factor models), and earnings volatility (standard deviation in time series pattern of earnings) for US corporations. For example, Srivastava and Tse (2016) show that successive cohorts undertake persistently higher research and development and compete with more knowledge-based business models.

The theory for systematic differences across cohorts comes from the theoretical arguments of Stinchcombe (1965), Christensen (1997), and Yip (2004). We expect that each new cohort would mimic the industry's time patterns in a more pronounced manner than older cohorts.

Hence, we offer H2.

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

4. Sample selection

Our data set includes chartered banks in the United States that have available financial data from 1976 to 2019.[8] 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 data on balance sheet, income statement, risk-based capital measures, and off-balance sheet items. Due to mergers and acquisitions, new entries, 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 nonmissing 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).[9] 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 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 nonbanking studies (e.g., Brown & 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 a cohort's observations from its formation years, retaining only those observations following that cohort's complete formation. 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 3600 in 2019. This fall can be attributed to mergers between banking companies and the consolidation of the banking industry (Berger & Bouwman, 2009) as well as bank failures. Moreover, this decline in the number of banks could be associated with banking crises and regulatory changes (Berger, Kashyap, & Scalise, 1995). Columns (2) to (6) of Table 1 present 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.

5. Definition and measurement of key variables

We employ various proxies for banks' business models.

5.1. Proxies for business models

We examine liquidity and credit risks, the two principal factors determining the survival of a bank (Imbierowicz & Rauch, 2014). These risks represent proxies for firms' business models in this study.

5.1.1. 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, Roulet, & Tarazi, 2013; Khan et al., 2017). The advantage of using this indicator is that it combines different sources of liquidity in one measure (Berger & 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 activities classified as "semiliquid," because they have no significant 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:

$$\begin{aligned} \mathit{Liquidity\,Creation} = & [0.5\,(\text{Illiquid Assets} + \text{Liquid Liabilities} \\ & + \text{Illiquid Guarantees}) - 0.5\,(\text{Liquid Assets} \\ & + \text{Illiquid Liabilities} + \text{Liquid Guarantees and Derivatives})] \\ & /\text{GTA} \end{aligned} \tag{1}$$

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

5.1.2. 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 prior studies as a measure of bank risk (e.g., Berger et al., 2016; Berger & Bouwman, 2009, 2013; Khan et al., 2017).[10] All banks report their risk-weighted assets in Call Reports from 1990 because Basel I risk-based capital requirements became effective in December 1990.[11] The description of credit risk measure is provided in Appendix 2.

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

[9] 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.

[10] 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.

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

Table 1
Sample description.

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	1585				12,686	−3.50	
1981	11,102	1586				12,688	−3.01	
1982	11,096	1590				12,686	−1.40	
1983	11,085	1585				12,670	3.38	
1984	10,698	1539				12,237	11.24	
1985	10,502	1479				11,981	10.81	
1986	10,232	1408				11,640	11.18	
1987	9893	1286				11,179	11.42	
1988	9439	1168				10,607	11.13	
1989	9115	1104				10,219	10.57	
1990	8834	1043	1795			11,672	12.26	
1991	8560	989	1706			11,255	12.80	
1992	8361	935	1626			10,922	14.45	57.13
1993	8154	878	1513			10,545	15.72	57.45
1994	7835	828	1423			10,086	17.40	59.27
1995	7437	762	1324			9523	15.25	59.60
1996	7087	702	1208			8997	16.16	61.63
1997	6691	646	1120			8457	16.60	62.16
1998	6338	598	1006			7942	16.54	62.00
1999	6087	554	915			7556	18.89	63.96
2000	5776	522	837	1044		8179	19.77	65.83
2001	5576	493	777	991		7837	20.78	65.93
2002	5429	466	730	940		7565	21.36	65.65
2003	5323	454	694	889		7360	22.96	65.95
2004	5190	429	635	842		7096	24.80	67.26
2005	5020	411	609	792		6832	25.42	68.48
2006	4877	387	569	722		6555	24.91	69.24
2007	4721	371	535	676		6303	24.82	70.17
2008	4575	356	500	628		6059	24.58	70.03
2009	4462	344	469	583		5858	24.03	68.03
2010	4352	321	424	527	1006	6630	24.84	66.63
2011	4284	305	402	497	952	6440	24.85	64.43
2012	4609	312	429	498	942	6790	24.67	62.90
2013	4484	294	406	465	877	6526	26.84	64.21
2014	4330	283	381	430	813	6237	27.98	64.92
2015	4177	267	355	392	739	5930	29.64	66.70
2016	4037	259	330	368	682	5676	31.26	67.56
2017	3909	245	318	339	632	5443	32.24	68.11
2018	3756	240	307	312	570	5185	28.30	68.83
2019	3627	220	293	292	520	4952	27.93	68.46
CADR	−2.57%	−4.94%	−6.06%	−6.49%	−7.07%			
Trend rate							0.767 ($p < 0.01$)	0.317 ($p < 0.01$)

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.

5.2. Variables representing operating strategy

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

5.2.1. Brokered deposits

Banks increasingly rely on brokered deposits, instead of core deposits, as a source of their funding (Berger & Bouwman, 2013; Cole & White, 2012). Consequently, we expect successive cohorts to exhibit an increasing concentration of these deposits. Brokered deposits are expensive in terms of interest costs and brokerage commissions and, therefore, must be invested in high-risk assets to cover their higher costs (Berger & Bouwman, 2013). 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. As such, failed banks are more likely to have brokered deposits than solvent ones (Goldberg & Hudgins, 2002).[12] *BDGTA* is measured by dividing brokered deposits by GTA.

5.2.2. Commercial real estate loans

Commercial real estate loans are given to finance acquisition, development, and construction of real estate-based income-producing properties such as retail malls, shopping centers, office buildings and

[12] 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 only well and adequately capitalized banks.

complexes, and hotels. The payback prospects from these assets 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 percentage 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 global 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 multifamily (five or more) residential properties, and real estate loans secured by nonfarm, nonresidential properties] by GTA.

5.2.3. 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 increased such 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.[13] Off-balance sheet items are used not only to generate additional income but also to reduce banks' monitoring costs, avoid capital adequacy requirements, exploit regulatory arbitrage, and elude taxation (Diamond, 1984; Flannery, 1998; Papanikolaou & Wolff, 2014; Pennacchi, 1988). However, these items can increase risk, with costs that ultimately are borne by insurance bodies such as FDIC. Notably, 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 & Berger, 1991). *OBSGTA* is measured by dividing off-balance sheet items (unused commitments on the asset side and derivatives) by GTA.

5.2.4. 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 US banks increased from 10% in 1983 to 35% in 2013 (FDIC data). This transition from traditional interest income sources has been facilitated by innovations in information, communications, and financial technologies and is supported by the need for banks to face competition from nonbanking financial institutions (Demirgüç-Kunt & Huizinga, 2010).

Revenues from nontraditional activities tend to be more volatile than traditional interest-based income (DeYoung & Torna, 2013). De Jonghe (2010, p. 387) concludes that "the heterogeneity in extreme bank risk is attributed to differences in the scope of non-traditional banking activities: noninterest 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).

5.3. 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.[14]

6. Tests of hypotheses

6.1. Hypothesis 1

To identify the time series trends in banks' business models, we compute the cross-sectional averages on an annual basis from 1976 to 2019 for liquidity risk and from 1992 to 2019 for credit risk. Column (8) of Table 1 and Panel A of Fig. 1 show that the liquidity risk increased over time, from −1.35% in 1976 to 27.93% in 2019. It is higher in each new decade than in the previous one. 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 global 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 a *p*-value 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 US banks increased between 1993 and 2003, and Delis et al. (2014), who make a similar assertion.

Results are also consistent with steady changes in banks' business models over time.

6.2. Hypothesis 2

Following prior studies that examine the cohort phenomenon in the nonbanking corporate sector (Brown & Kapadia, 2007; Srivastava, 2014; Srivastava & Tse, 2016), 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. 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).[15] We then calculate the average for a cohort by averaging its cohort-year averages.

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 the statistical significance of the differences between

[13] The Basel Accord risk-based capital standards were implemented in 1990 to correct the issues 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).

[14] 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.

[15] 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 US banks started to report it in Call Reports in 1990.

Table 2
Average financial characteristics of successive cohorts of banks 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
Panel A: Cohort-wise averages characteristics and risks and inter-cohort differences								
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								
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	

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.

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 is not significant.

Averages for *Growth* 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 averages for profitability 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 but have 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 the last two differences for *NIIOI* are not significant.

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

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

where *Characteristic* is a measure of risk, calculated on a cohort-year basis and 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.

6.2.1. Examining cohort risk 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 of observations (2011 to 2019), and the average for the established banks is calculated using 44 years of observations (1976 to 2019). Thus, the pre-1970 cohort's average includes the earliest years' observations from the sample period, with economic characteristics that could differ from those of recent years. Thus, the average inter-cohort differences could simply represent the overall time trends.

Figure 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):

$$\begin{aligned}\text{Characteristic}_{\text{Cohort,Year}} = {} & \gamma_0 + \gamma_1 \times \text{Year} + \gamma_2 \times \text{Dum1970s} + \gamma_3 \times \text{Dum1980s} \\ & + \gamma_4 \times \text{Dum1990s} + \gamma_5 \times Dum2000s + \varepsilon_{Cohort,year}\end{aligned} \tag{3}$$

Characteristic is a measure of risk, calculated on a cohort-year basis. γ_1 captures the time trend. *Dum1970s*, *Dum1980s*, *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. The purpose of this model is twofold. First, an increasing or decreasing pattern in coefficients on successive dummies would indicate a systematic pattern in characteristics of successive cohorts, despite controlling for the overall time trends. Second, the difference in magnitudes of coefficients of successive dummies would indicate that successive cohorts are systematically different from each other.

Table 3 reports results for Eq. (3). Column (3) shows that despite controlling for time trends, the coefficients on successive dummies (*Dum1970s*, *Dum1980s*, *Dum1990s*, and *Dum2000s*) are generally increasing: 2.168, 3.701, 8.813, and 8.569, each significant at a *p*-value 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).

Table 3
Time series and cohort trends in bank risks.

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

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.

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

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 1000). 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.

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 a *p*-value 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. These results are consistent with Christensen's (1997) theory that older organizations suffer from more rigid organizational structures and display inertia in their inability to keep up with disruptive innovations introduced by newcomers.

6.2.2. 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 generally 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 the second case, the value for the 2000s cohort is higher than for the 1990s cohort.

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

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

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 Columns (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).

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

Table 4
Time series and cohort trend in bank risks, after controlling for operating characteristics.

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)
Panel A: *Credit Risk*											
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*	
Panel B: *Liquidity Risk*											
Year × 1000	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	

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

$$\text{Risk}_{\text{cohort, year}} = \beta_0 + \beta_1 \times \text{Year} + \beta_2 \times \text{Characteristic}_{\text{cohort; year}} + \gamma_1\,\text{Dum1970s} + \gamma_1\,\text{Dum1980s} + \gamma_2\,\text{Dum1990s} + \gamma_3\,\text{Dum2000s} + \varepsilon_{\text{cohort, year}},$$

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 1000). 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.

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. Importantly, what we document as cohort patterns in business models, using proxies of liquidity and credit risks, are also apparent in proxies for operating strategy.

7. 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 & Bouwman, 2013). However, because of imperfections in the market, competitive structures, and differential regulatory requirements, bank size could be related to liquidity risk (e.g., Berger & Bouwman, 2009; Kashyap, Rajan, & Stein, 2002) and credit risk (e.g., Hakenes & Schnabel, 2011; Stiroh, 2004). We follow Imbierowicz and Rauch (2014) to define the bottom 25% of GTA as small banks, the top 25% as large banks, and the middle 50% 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 1238 large banks in 2019 are pre-1970s, showing that reaching the top bank size takes a long time. Nevertheless, a nontrivial number of large banks from the other cohorts also become large banks. 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.

7.1. 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 global financial crisis, and then resumed their upward trend. Fourth, the divergence between small and large banks has increased over time, particularly for credit risks.

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.

7.2. Cohort patterns by size categories

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.

To formally examine cohort patterns by size segments, we estimate Eq. (3) by three size categories. 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 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 rising pattern. 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). This result goes contrary to the theory suggesting that larger organizations are least amenable to changes with time (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,

Table 5
Cohort-wise sample description across bank size categories.

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	2779	2779					5556	5556					2778	2778				
1977	2779	2779					5557	5557					2778	2778				
1978	2776	2776					5552	5552					2775	2775				
1979	2776	2776					5552	5552					2775	2775				
1980	3172	2510	662				6343	5552	791				3171	3039	132			
1981	3172	2556	616				6344	5529	815				3172	3017	155			
1982	3173	2597	576				6342	5506	836				3171	2993	178			
1983	3168	2642	526				6335	5474	861				3167	2969	198			
1984	3060	2587	473				6118	5268	850				3059	2843	216			
1985	2996	2556	440				5990	5174	816				2995	2772	223			
1986	2910	2511	399				5820	5033	787				2910	2688	222			
1987	2796	2432	364				5589	4867	722				2794	2594	200			
1988	2652	2329	323				5304	4666	638				2651	2444	207			
1989	2555	2268	287				5110	4510	600				2554	2337	217			
1990	2918	2061	242	615			5836	4329	560	947			2918	2444	241	233		
1991	2814	2048	244	522			5628	4168	512	948			2813	2344	233	236		
1992	2731	2051	227	453			5461	4038	478	945			2730	2272	230	228		
1993	2638	2047	203	388			5271	3924	454	893			2636	2183	221	232		
1994	2522	1995	187	340			5043	3763	430	850			2521	2077	211	233		
1995	2381	1931	166	284			4762	3582	399	781			2380	1924	197	259		
1996	2250	1868	146	236			4498	3408	369	721			2249	1811	187	251		
1997	2115	1799	124	192			4228	3227	341	660			2114	1665	181	268		
1998	1986	1712	108	166			3971	3081	314	576			1985	1545	176	264		
1999	1889	1635	99	155			3778	2985	292	501			1889	1467	163	259		
2000	2045	1529	90	133	293		4090	2795	255	441	599		2044	1452	177	263	152	
2001	1960	1531	90	121	218		3918	2677	234	404	603		1959	1368	169	252	170	
2002	1892	1518	92	116	166		3782	2602	212	375	593		1891	1309	162	239	181	
2003	1840	1506	91	113	130		3680	2570	201	341	568		1840	1247	162	240	191	
2004	1774	1489	87	93	105		3548	2521	192	314	521		1774	1180	150	228	216	
2005	1708	1463	85	80	80		3416	2458	176	309	473		1708	1099	150	220	239	
2006	1639	1411	80	79	69		3278	2399	165	289	425		1638	1067	142	201	228	
2007	1576	1371	71	73	61		3152	2331	168	262	391		1575	1019	132	200	224	
2008	1515	1314	72	72	57		3030	2280	156	236	358		1514	981	128	192	213	
2009	1465	1269	70	74	52		2929	2226	149	227	327		1464	967	125	168	204	
2010	1658	1266	67	68	57	200	3315	2054	140	201	267	653	1657	1032	114	155	203	153
2011	1610	1239	65	68	57	181	3220	2033	132	192	252	611	1610	1012	108	142	188	160
2012	1698	1304	71	69	60	194	3395	2232	136	206	255	566	1697	1073	105	154	183	182
2013	1632	1276	69	68	56	163	3263	2180	127	191	234	531	1631	1028	98	147	175	183
2014	1560	1236	69	61	51	143	3118	2105	119	185	225	484	1559	989	95	135	154	186
2015	1483	1188	69	59	43	124	2965	2046	111	168	206	434	1482	943	87	128	143	181
2016	1419	1140	67	58	46	108	2838	1999	108	155	186	390	1419	898	84	117	136	184
2017	1361	1098	62	59	47	95	2722	1954	107	148	159	354	1360	857	76	111	133	183
2018	1297	1059	63	56	42	77	2592	1873	103	145	144	327	1296	824	74	106	126	166
2019	1238	1029	58	55	36	60	2476	1809	92	139	136	300	1238	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

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.

Table 6
Time series and cohort trend in bank risks, by size categories.

Variable	Time trend				Time trend and cohorts			
	All	Small	Medium	Large	All	Small	Medium	Large
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Credit Risk								
Year × 1000	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 × 1000	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

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 1000). 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.

and technological capabilities that larger old cohorts possess better than smaller old cohorts. However, we observe only those banks that survive and remain large. Thus, another plausible explanation is that only those banks that change with time and can keep up with evolving business models are likely to survive and retain market share.

7.3. Cohort patterns by size categories, 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 turns time trends and cohort dummies negative across all size categories with a substantial increase in *R*-squared values.

Results for liquidity risk are less pronounced. 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 banks and the time trend becomes insignificant for medium and large banks. This suggests that changing operating strategies across cohorts and over time significantly explains the cohort trends for small banks and the time trend in liquidity risk for large banks.

8. 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 cohorts. We find results consistent with this idea, reported in Panels A and B of Fig. 6, which

Table 7

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

Variable	Control for *BDGTA*			Control for *CRELGTA*			Control for *OBSGTA*			Control for *NIIOI*			All factors		
	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)
Panel A: *Credit Risk*															
Year × 1000	−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*
Panel B: *Liquidity Risk*															
Year × 1000	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

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 1000). 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.

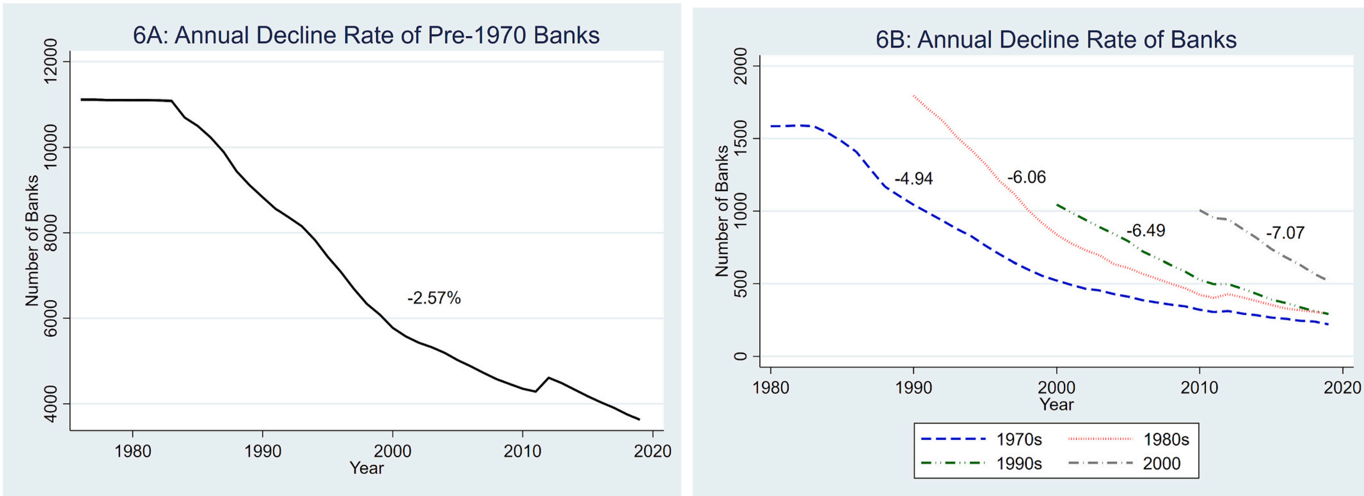

Fig. 6. Cohort-wise compound annual decline rate of banks.
Banks are divided into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as new banks. All banks opened in a common decade are considered part 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). (6 A) 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.

plots the number of banks in each cohort over time.[16] The compound annual diminishment rate (CADR) or the downward slope is a measure of attrition rate over time, resulting from bank failures, mergers, or acquisitions (Berger, Demsetz, & Strahan, 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.

Aggressive business strategies might fuel growth during boom times but could backfire during downturns. Prior literature (Acharya & Mora, 2015; Imbierowicz & Rauch, 2014) argues that credit and liquidity risks, in particular, would exacerbate the failure likelihood of banks during a negative shock to the wider economy. On one hand, banks would face large-scale client defaults. On the other hand, they would find it difficult to meet their own short-term obligations. We test this idea following the black swan event of the global 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 the 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.

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

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

9. Conclusion

In this study, we test the theories on organizational change in the setting of US banks. We examine time series changes in two proxies of banks' business models, namely, liquidity and credit risks, that are associated with bank failures. We find a steady increase in liquidity risk over the last 40 years or so. Credit risk also increases but declines briefly after the global fiscal crisis and then 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 risk-taking by legacy banks in response to newer cohorts' strategies. In addition, this pattern is related to riskier operating strategies adopted by the entire spectrum of bank cohorts, but more so by newer cohorts, that is, with 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 size categories. An examination across categories leads to new insights. The average risks of large banks are increasing at a faster rate than for small banks. But large banks from old cohorts seem to adopt riskier strategies and are keeping pace with the market much better than smaller banks from the old cohorts are.

In sum, the paper throws light on Schumpeter's idea of technological progress and creative destruction. Our results show a steady change in business models of the US banks over time, which is largely because of innovations introduced by the incomers. Old cohorts must change their business models to survive. They are unable to do so at the same pace as newer cohorts, consistent with Christensen (1997). Surprisingly, and contrary to Christensen (1997), large established firms display the fastest change over time in keeping up with newer cohorts. Arguably, results indicate that larger banks have the necessary resources, talent, and capabilities to change and are better at changing over time. Another

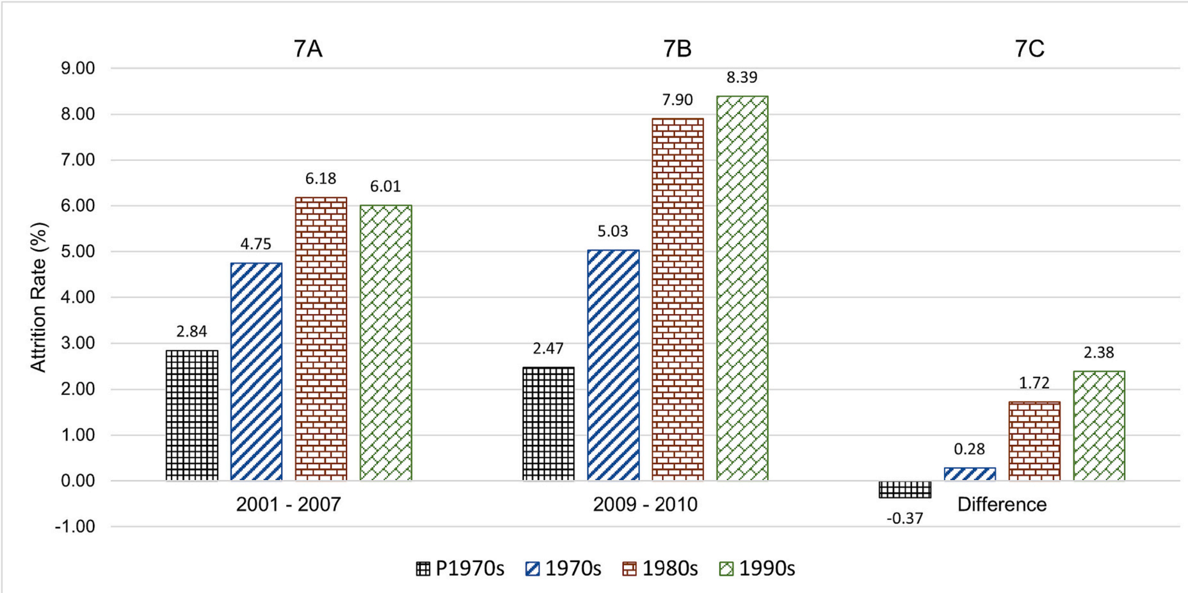

Fig. 7. Cohort-specific sample attrition rate following the 2008 financial crisis.
Banks are divided into five cohorts based on their year of opening. Banks with an opening year before 1970 are classified as pre-1970 banks. The remaining banks are classified as new banks. All banks opened in a common 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 figs. (7 A 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: 7 A 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 7 A.

plausible explanation is that because we observe only survivors, those that change can endure better while retaining market shares.

The results of this paper are consistent with the idea that large banks remain large decade after decade, indicating a high degree of entrenchment. Newcomers must adopt riskier and riskier strategies to gain any market share. This is unlike many capital-intensive service sectors, such as hotels and telecommunication, that have been disrupted by modern innovations. Stylized facts we document must interest regulators and policymakers. The welfare implications of this change, or lack of change in the large-size category, are left to future studies.

Appendix A. 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 & 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 B. 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.
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.

Panel A: Liquidity classification of bank activities

Assets	
Illiquid assets (weight = ½)	Liquid assets (weight = −½)
Commercial real estate loans (CRE)	Cash and due from other institutions
Loans to finance agricultural production	All securities (regardless of maturity)
Commercial and industrial loans (CandI)	Trading assets
Other loans and lease financing receivables	Fed funds sold
Other real estate owned (OREO)	
Investment in unconsolidated subsidiaries	
Customers' liability on bankers' acceptances	
Intangible assets	
Premises	
Other assets	
Liabilities and equity	
Liquid liabilities (weight = ½)	Illiquid liabilities + equity (weight = −½)
Transactions deposits	Bank's liability on bankers' acceptances
Savings deposits	Subordinated debt
Overnight federal funds purchased trading	Other liabilities
Trading liabilities	
Off-balance sheet	
Illiquid guarantees (weight = ½)	Liquid guarantees and derivatives (weight = −½)
Unused commitment	Net participations acquired
Net standby letters of credit	Interest rate derivatives
Commercial and similar letters of credit	Foreign exchange derivatives
All other off-balance sheet liabilities	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)]

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