Financial Statements not Required*

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October 2023

* For helpful comments, we thank an anonymous reviewer, Ray Ball, Mary Barth, Jannis Bischof, Travis Chow, Mark DeFond (discussant), Richard Frankel, Joao Granja, John Hand, S.P. Kothari, Mark Lang (Editor), Maria Loumioti (discussant), Matthew Pritsker, Rui Silva, Tom Ware, several lenders and bank supervisors who wished to remain anonymous, and seminar participants at the Bocconi Accounting Symposium, Columbia Business School, the Dopuch Accounting Conference at Washington University in St. Louis, Hong Kong University, INSEAD, the LBS Accounting Symposium, Maastricht, Mannheim, and Vrije Universiteit Amsterdam. Thomas Barry provided excellent research assistance. We thank the Risk Management Association and Tom Holt for providing the Annual Statement Studies data and many helpful discussions. The authors acknowledge financial support from their respective institutions. Minnis acknowledges support from the Chookaszian Accounting Research Center and Charles E. Merrill Trust Endowment Fund. Sutherland acknowledges support from the Head Family Fund for research in Economics, Finance, and Accounting at MIT Sloan. Vetter acknowledges financial support from Deutsche Forschungsgemeinschaft - Project-ID 403041268 - TRR 266.

Declarations of Interest: Minnis is a member of the Financial Accounting Standards Board Private Company Council. Sutherland is a member of the Equipment Leasing & Finance Foundation Research Committee. No organization reviewed, approved, or provided compensation for this paper or its analysis.

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Abstract

Using a dataset covering 3 million commercial borrower financial statements, we document a substantial, nearly monotonic decline in banks' use of attested financial statements (AFS) in lending over the past two decades. Two market forces help explain this trend. First, technological advances provide lenders with access to a growing array of borrower information sources that can substitute for AFS. Second, banks are increasingly competing with nonbank lenders that rely less on AFS in screening and monitoring. Our results illustrate how technology adoption and changes in credit market structure can render AFS less efficient than alternative information sources for screening and monitoring.

JEL Classification: G21, G23, M41, M42, D82, G30, O31
Keywords: banks, lending standards, financial statements, auditing, private firms, SME lending, nonbank lending, fintech.

1 Introduction

"In general, of course, it will pay the owner-manager to engage in bonding activities and to write contracts which allow monitoring as long as the marginal benefits of each are greater than their marginal cost" (Jensen and Meckling 1976).

Positive accounting research argues that attested financial statements (henceforth AFS) emerge in markets not only because of regulation, but also because they provide an efficient method for capital suppliers to monitor managers (Watts 1977; Watts and Zimmerman 1983; Kothari, Ramanna, and Skinner 2010; Ball 2022). An implication of this is that innovations in information sources can reduce demand for AFS in markets where they are not mandated. Similarly, if lenders differ in their screening and monitoring reliance on AFS (e.g., Berger, Minnis, and Sutherland 2017), and the mix of lenders in the economy changes, borrowers may face less demand for AFS.

Evidence on such developments is important to understanding both the future of CPA services and how firms access credit. In this paper, we examine recent technological advances and credit market structure changes in the private firm lending market to understand the implications for AFS demand in a setting where reporting and auditing are voluntary.

We begin by studying the propensity for U.S. banks to collect AFS as part of their screening and monitoring of private firms between 2002 and 2017. We access data from the Risk Management Association (RMA) containing financial statement collection records of banks responsible for over half the U.S. commercial lending market. The data cover nearly 3 million business financial statements, categorized by financial statement type, bank, and borrower industry, location, and size. While prior studies examine cross-sectional variation in this data (e.g., Lisowsky, Minnis, and Sutherland 2017; Berger et al. 2017; Di and Pattison 2020), we focus on the time series. Figure 1 reports a striking descriptive finding: in 2002, 57% of statements provided were an unqualified audit, review, or compilation (i.e., AFS), and this rate declines to 33% in 2017.

This trend does not appear to be a simple manifestation of changes in the types of borrowers (e.g., Srivastava 2014) or banks in the data. Specifically, in subsequent figures we plot the year fixed effects from regressions modeling AFS collection after controlling for borrower characteristics (industry, location, and size) and bank fixed effects, and limiting the sample to banks sharing data with RMA every year. We find little change in the 2002-2017 AFS decline compared to Figure 1, and the decline is present in all three AFS report types (unqualified audits, reviews, and compilations). Additionally, the continual nature of the decline does not align with explanations based on one-time changes in regulation or accounting standards alone. Together, this evidence suggests that the large AFS decline we find does not stem from sample composition changes or single events. We therefore turn to examining the hypothesis that ongoing changes in the lending marketplace play a role in explaining AFS collection declines.[1]

Our focus is on technology adoption and nonbank lending as the relevant marketplace developments, motivated by two stylized facts. First, sweeping advances in computing power, data management, and data analytics have spawned new information sources that have transformed how lenders screen and monitor (ELFF 2023). For example, information sharing technologies have proliferated as the costs of gathering and verifying information have declined, leading to more timely and comprehensive credit reports (Djankov, McLeish, and Shleifer 2007; Liberti, Sturgess, and Sutherland 2022). Tellingly, PayNet, a leading U.S. credit bureau, advertises its credit score and credit report products using the slogan "Financial statements not required."[2] Other vendors promote their products as helping lenders quickly make approval decisions using alternative data or just financial statement components rather than complete, externally verified financial

[1] We also find little evidence of securitization explaining the trend. The securitization market for SME loans is quite small, both compared to total SME lending and to other credit markets (e.g., mortgages or credit cards) (Wilcox 2011). Additionally, when the securitization markets froze during the financial crisis, our downward trend continued.
[2] According to its website, PayNet (acquired by Equifax in 2019) has the "largest proprietary database of small business loans, leases, and lines of credit in existence" and has attracted eight of the ten largest lenders as members.

statements.[3] Section 3.3 provides further accounts from vendors, lenders, and regulators explaining how technology can substitute for AFS.

Second, nonbank lenders including captives, independent finance companies, and fintechs have grown considerably, and according to Gopal and Schnabl (2022) now provide the majority of U.S. small business loans. Whereas banks must demonstrate their credit standards to regulators, by, for example, collecting current financial statements or other documents from borrowers (Basel 2000; Granja and Leuz 2018; OCC 2020), nonbanks face no such oversight. Because AFS are costly to produce, competition between banks and nonbanks can influence the demand for AFS in credit markets.

Of course, documenting a role for technology adoption or nonbank lending in the AFS decline requires analyses that hold constant the overall state of the economy, accounting standards, and other factors that can independently affect AFS collection. For technology adoption, we therefore examine how AFS demand responds to one specific technological advance: the evolution of the PayNet credit bureau, as measured by the share of lending in an industry-state-year by its lender members. Intuitively, endogenous credit bureau technology adoption by lenders should reduce demand for AFS. A key advantage of this approach is that it permits us to study pertinent technology adoption in a granular way. To illustrate, the bureau provides information designed to substitute for AFS (hence the "financial statements not required" slogan). Additionally, bureau information coverage evolves sporadically because lenders join in a staggered pattern and lenders often specialize by sector or equipment type (i.e., the technology shocks we study are not common to all industries or locations within a year). We find the share of loans made by PayNet member lenders is negatively associated with AFS collection by banks. Roughly one-tenth of the AFS

[3] To illustrate, Enigma helps lenders analyze a borrower's credit card receipts and transaction volumes. Tax Status enables lenders to instantaneously pull a borrower's complete tax return history from the IRS. Rutter allows lenders to fetch data from a borrower's accounting platforms.

decline we document in Figure 1 can be traced to the propagation of this single alternative information source.

For nonbank lending, we investigate the extent to which banks and nonbanks rely on AFS in lending, and how this is changing over time. Recent evidence points to nonbanks using different contracting strategies than banks (Chernenko, Erel, and Prilmeier 2022; Gopal and Schnabl 2022; Loumioti 2022). Although this work leverages changes in bank regulation or supervision for exogenous bank lending capacity variation, our research question requires a different approach because such variation by design directly affects lending standards, including AFS collection. Therefore, we study local CPA supply shifts, and measure changes in bank lending using nonbank lending as a benchmark to control for local economic conditions and credit demand. Our assumption is that if AFS are more important to banks given their screening and monitoring approach, then bank credit should change more than nonbank credit when CPA supply shifts. To test this, we assemble a comprehensive dataset of Uniform Commercial Code (UCC) filings detailing nearly 12 million secured non-real estate business loans and leases since 1997. The dataset covers both bank and nonbank lenders, including captives like John Deere and Volvo, and independent finance companies like GE Capital. We identify CPA firms using state license information (Vetter 2022).

In a fixed effects specification controlling for local economic conditions and credit demand (county-year fixed effects), and separate time effects for different lender types (lender type-year fixed effects), we find that the sensitivity of lending to the number of CPA firms is far greater for banks than nonbanks. Economically, a one standard deviation increase in CPA supply is associated with a 0.18 standard deviation increase in bank originations, versus just a 0.09 standard deviation increase in nonbank originations (dollars of equipment financed by nonbanks). These results are consistent with banks being more reliant than nonbanks on AFS when screening and monitoring.

To confirm this inference, we study more extreme CPA supply shifts—instances where counties become or emerge from being a CPA desert (i.e., having zero CPA firms), and once again find a greater response for banks than nonbanks.

Having established that banks are more reliant on CPA services, we link this finding back to the trend of reduced AFS collection. We find that the sensitivity of bank lending to the supply of CPAs changes over time. We divide the 2000-2019 period into four 5-year periods (2000-2004, 2005-2009, 2010-2014, and 2015-2019) and re-estimate our model on each. In line with Figure 1, the sensitivity of bank lending to CPA supply diminishes by more than two-thirds from the first to last period. In other words, banks appear to be increasingly behaving like nonbanks with respect to their AFS demand. Similarly, the sensitivity declines most in counties where nonbank growth is greatest. Our findings are in line with competition shaping lending standards (e.g., Bushman, Hendricks, and Williams 2016; Lisowsky et al. 2017; Granja, Leuz, and Rajan 2022). Thus, as nonbanks have gained market share, banks have responded by reducing AFS requests, contributing to the downward trend we document.

Does the AFS decline result from a 'race to the bottom' in which competition compels banks to recklessly cut lending standards? Our final tests examine bank chargeoffs and profitability, and find little relation with AFS collection. We also note that while theory links heightened competition to reduced lending standards (Ruckes 2004; Dell'Ariccia and Marquez 2006), this is modeled as a business cycle phenomenon that reverts and not a persistent trend like the one we document. Thus, our AFS decline is most in line with explanations rooted in lenders finding AFS less cost efficient for screening and monitoring (e.g., Petersen and Rajan 2002).

Our findings make several contributions. First, we document an important descriptive fact: the use of AFS in the lending market has declined. This development cannot be explained by borrower composition changes or bank traits such as concentration or size explored in related work

(Berger et al. 2017; Lisowsky et al. 2017). While we investigate two candidate explanations for this trend, there are likely others which we think the literature should explore. For example, some practitioners have asserted that changes in GAAP have reduced the usefulness of AFS for private firms (Bradshaw et al. 2014), which have in turn opted to forgo unqualified audit opinions. As one CFO explains, "The growing trend toward more complex standards and disclosures under existing GAAP can be misleading or distracting to users of private company standards" (Financial Accounting Foundation 2011).

Second, we add to recent literature examining how technology is transforming accounting. This research has focused on how Artificial Intelligence, blockchain technology, and other tools interact with labor in audit firms (Law and Shen 2020; Ham et al. 2022). A common theme in this research and ours is that technology can reduce the demand for CPA services, which raises important questions about the future of the accounting profession.[4] Our findings suggest that technological tools are increasingly being relied upon to verify information in financial markets, and in doing so, displacing the role for traditional CPA services in our economy. While we focus on information sharing technology and credit scores, recent work explores other new timely information sources that can plausibly substitute for AFS collection, and these other sources are worthy of additional research.[5]

Third, our evidence also relates to accounting research studying the evolution of debt contracting over recent decades.[6] Demerjian (2011) and Ball, Li, and Shivakumar (2015) link changes in accounting standards to fewer accounting-based covenants in syndicated loan contracts.

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[4] See also discussions of the usefulness of accounting numbers (Lev and Gu 2016) and of accounting program enrollment declines (Gabbin, Irving, and Shifflett 2020).

[5] Lenders are expanding the types of information they access, including digital footprints (Berg et al. 2020), social media (Lin, Prabhala, and Viswanathan 2013; Costello, Down, and Mehta 2020), and collateral surveillance (Sutherland 2020).

[6] Our paper also relates to contemporaneous work finding that financial development during the 20th century reduced the prevalence of secured debt (Benmelech, Kumar, and Rajan 2020).

To our knowledge, our emphasis on the role of technology and credit market structure is unique, as is our investigation of private firm lending.

Finally, we contribute to work on how private firms access credit markets (Allee and Yohn 2009; Minnis 2011; Cassar, Ittner, and Cavalluzo 2015; Kausar, Shroff, and White 2016; Berger et al. 2017; Breuer, Hombach, and Müller 2017; Lisowsky and Minnis 2020; Badertscher et al. 2023). Recent research documents a growing role for nonbank lenders in serving private firms (Ma, Murfin, and Pratt 2022; Gopal and Schnabl 2022; Howell et al. 2022). However, we have little empirical evidence on the extent to which these lenders use AFS. Our results indicate that nonbanks rely less than banks on AFS; however, competitive interactions between nonbank and bank lenders are important to understanding AFS changes over the past two decades.

2 Background

2.1 Theoretical Framework

Commercial credit markets are characterized by imperfect information: borrowers have private information about their creditworthiness. Moreover, during a credit relationship the lender learns more than its rivals about the borrower (Sharpe 1990, Rajan 1992; Dell'Ariccia, Friedman, and Marquez 1999), leading to information asymmetries between lenders. Theoretical work describes two types of information collection activities that lenders engage in to mitigate this information asymmetry. First, lenders screen borrowers to infer their creditworthiness and determine whether and on what terms to extend credit. Screening can take the form of requesting, collecting, and verifying information as part of a credit application or offering a menu of contracts designed to separate borrowers according to their creditworthiness. Lenders cannot simply charge a high rate to compensate for their information disadvantage, as doing so can distort borrower sorting or effort incentives (Stiglitz and Weiss 1981).

Second, after extending credit, lenders monitor borrowers. Credit agreements are often accompanied by covenants that require the borrower to take or refrain from certain actions (Rajan and Winton 1995). For example, borrowers must make payments on their loan, and may also be required to furnish financial reports, maintain specified financial ratio levels, or not pay dividends. When covenants are violated, control shifts to the lender. Lenders then collect information throughout the loan to discern whether the borrower is compliant with the covenants.

Lenders monitor even in instances where covenant violation or default is not imminent, or when the loan is secured. To illustrate, if a borrower misses a payment, the lender must decide whether to grant an extension, renegotiate the loan, or declare the borrower in default and repossess any collateral. Lenders lose money when they grant extensions to insolvent borrowers or prematurely liquidate solvent ones. Therefore, the lender's ongoing monitoring efforts provide timely information about the borrower's prospects that prepares them for a variety of contracting scenarios. This monitoring is useful to both banks and nonbanks: Rajan and Winton explain, "Although we call the monitoring lender a bank for simplicity, in practice it could be any financial institution" (p. 1115).

Financial statements can aid both screening and monitoring. In terms of screening, income statements provide an indication of the borrower's ability to service the loan, whereas balance sheets provide a lower bound value estimate of pledged assets (Watts 2003; Gox and Wagenhofer 2009; Kothari, Ramanna, and Skinner 2010). As for monitoring, financial statements keep the lender informed of the borrower's performance and solvency, and can also be used in financial covenants to align borrower and lender interests (Christensen and Nikolaev 2012; Christensen, Nikolaev, and Wittenberg-Moerman 2016; Demerjian 2017; Dou 2020), though their application is uncommon among private firms lacking audits.[7] Besides fulfilling the lender's screening and

[7] Instead, contingent transfer of control rights tends to be based on repayment behavior (e.g., missing a loan payment, deferral requests, or default). Additionally, like their public borrower counterparts, private borrowers can also face negative covenants that restrict their ability to pay dividends, take on additional debt, or sell assets.

monitoring needs, borrower financial statements can be furnished to regulators supervising the lender's underwriting and risk management activities (this obviously does not apply to nonbanks).

However, financial statements also have limitations. First, borrower management has incentives to overstate their creditworthiness, and therefore financial statement disclosures cannot necessarily be taken at face value. Borrowers can obtain independent verification from a CPA firm, which increases the quality of the financial statement information. But doing so is costly and privately held borrowers are not otherwise mandated to produce them. As a result, the use of AFS in lending relationships can be understood as the outcome of bargaining between the lender and borrower. If the lender's reporting requests are too onerous, the borrower can shop around just as they would if the lender had quoted a high interest rate, and thus credit market competition influences AFS provision.

A second limitation is that financial statement informativeness is contingent upon timeliness, as the borrower's ability to pay can rapidly change. CPA verification delays the provision of financial statements. As one banker explained to us, "While audited financial statements are useful, they come six months too late." An additional timeliness issue is that GAAP financial statements are based on historical costs rather than values, though in recent years accounting standards have changed to increase emphasis on fair value accounting.

Financial statements are not the only form of information that lenders can rely upon when screening and monitoring. Firms must report their sales, expenses, assets, and liabilities to the IRS annually, and hence tax returns can provide a less costly substitute for complete financial statements (Minnis and Sutherland 2017). A lender's prior experience and industry or collateral expertise can serve as another information source (Berger et al. 2017). Thus, the screening and monitoring usefulness of AFS can depend on a given lender's organizational features and type (e.g., diversified bank vs. the captive financing arm of an equipment manufacturer).

Credit reports provided by credit bureaus are also commonly used by lenders (Cassar et al. 2015). In terms of a screening tool, credit reports offer a detailed account of the borrower's payment history, which is informative for determining whether the borrower can service the loan they applied for. As for monitoring, credit reports allow the lender to observe any new loans that the borrower has with other creditors, the payment status of these loans, in addition to assets that the borrower has pledged as collateral.

Each of these alternative information sources also have limitations, particularly related to contractibility and verification. It is difficult, if not infeasible to contract on a lender's expertise or soft information, or on a tax return when the inputs are not verifiable. Credit scores are calculated based on a wide variety of inputs, and the calculation and inputs can change regularly, rendering it impractical to contract on them. Additionally, when lender-borrower information asymmetry is high, such as when the relationship is new or when alternative information sources require additional validation, AFS can be beneficial (Minnis and Sutherland 2017).

Credit bureau coverage of individuals and firms has expanded over the past twenty years (World Bank, 2019a, 2019b). This is arguably a manifestation of several developments. First, economy-wide advances in computing power, data management, and data analytics have reduced the cost of producing credit reports and credit scores. As a result, credit bureaus can deliver increasingly timely, comprehensive, and robust information to lenders. These same technological advances have spawned an array of other screening and monitoring tools including those based on social media (Lin, Prabhala, and Viswanathan 2013; Costello et al. 2020), digital footprints and nonstandard information (Iyer et al. 2016; Berg et al. 2020), and Application Programming Interfaces (APIs) that link into payment processors or the borrower's accounting platform. These new tools can be based on previously uncollected data or soft information that has been "hardened" by modern linguistic techniques (e.g., sentiment analysis of social media, customer reviews, or loan officer notes) (Liberti and Petersen 2019; Campbell, Loumioti, and Wittenberg-Moerman 2019; Liu 2022).

Second, as the costs of producing credit reports have fallen, more lenders have adopted them, leading to network effects that further encourage adoption and improve information coverage (Liberti et al. 2022) (credit reports arise from lenders voluntarily sharing their contract and payment information with a credit bureau). Third, changes in the CPA regulatory landscape including the Sarbanes-Oxley Act, 150-Hour Rule, and peer review mandates have made AFS more costly for CPA firms to provide. This in turn can induce the endogenous development of alternative information sources, as lenders pursue more cost-effective screening and monitoring tools. Such advances can be understood more generally through the lens of task automation that displaces costly labor performing routine tasks (Acemoglu and Restrepo 2019).

Overall, our theoretical framework illustrates a) why lenders seek information to screen and monitor borrowers, b) the potential role for AFS in lending, and c) how technological advances and regulatory developments can obviate the need for AFS in lending. Moreover, one of the key advantages of studying privately held firms is that the provision of financial statements is an equilibrium outcome of borrower-lender bargaining largely sheltered from regulatory mandates: banks and borrowers agree on reporting terms conditional on costs and benefits.[8] Key to our study is that as the costs and benefits change over time, we expect the equilibrium provision of AFS to also change over time.

2.2 Setting: Contracts and Lender Types

Our technology adoption and nonbank lender tests study the U.S. secured commercial lending market, where borrowers access credit for agricultural, construction, logging,

[8] Among others, see Blackwell, Noland, and Winters (1998), Allee and Yohn (2009), Minnis (2011), Cassar et al. (2015), Lisowsky et al. (2017), Minnis and Sutherland (2017), Berger et al. (2017) and Minnis and Lisowsky (2020).

manufacturing, medical, office, transportation, and other equipment. According to Gopal and Schnabl (2022), annual originations in this market average $700 billion in recent years, representing over 70% of all small business lending. Contracts can be organized into two broad categories: leases (where the lender retains ownership of the equipment and agrees to rent it to the borrower for a specified period) and loans (where the borrower obtains legal ownership of the equipment after making all contractually required payments). Loans and leases also differ in the services provided by the lender (Contino 1996; Murfin and Pratt 2015) and their tax, bankruptcy, and financial reporting treatment (FASB 2016). Screening and monitoring efforts are important for both contract types, as lenders tend to retain the equipment finance contracts they originate.[9]

The secured credit market is served by both bank and nonbank lenders. These lenders differ in their business model and regulation. Banks tend to serve a broader set of clients (including households, private and public firms, and farms) and offer a wider range of financial services (including deposits, trusts, financial planning, mortgages, credit cards, and loans).

Despite variation in both contract forms and lender types, AFS are a common screening and monitoring tool. A popular equipment finance textbook (Contino 1996) explains:

> Lessors sometimes monitor a lessee's financial condition during the lease by requiring that the lessee *periodically* submit financial reports, such as current balance sheets and profit and loss statements. With these, lessors can often spot potential financial problems and take whatever *early action* may be necessary to protect their investment… in some transactions, *the reporting requirement may be burdensome, and if so, it should be reduced or eliminated* (emphasis added).[10]

3 Data and Summary Statistics

3.1 Data

[9] As one Federal Reserve white paper explains, "In contrast to the widespread securitization of consumer credit, securitized pools consisting solely of small business loans (SBLs) are relatively rare, perhaps because it is difficult to deal with the great heterogeneity in business loans and in the collateral that might be repossessed in the event that those loans default" (Wilcox 2011).

[10] Similarly, GE Capital, one of the largest lenders in the 1990s and 2000s, provides the following guidance in their credit handbook: "A lender customarily confirms financial and collateral information provided by the borrower in order to support ongoing loan requests" (GE Capital Commercial Finance 1999).

To examine AFS collection, we access data from the Risk Management Association (RMA). Founded in 1914, RMA is a non-profit industry association whose "sole purpose is to advance the use of sound risk management principles in the financial services industry."[11] RMA organizes credit risk and enterprise risk courses, and provides databases and benchmarking tools to benefit its over 1,600 financial institution members. Perhaps their most prominent tool (and our main source of data) is the RMA Annual Statement Studies, first published in 1919, which contains summary statistics from borrower financial statements collected by its member banks. The purpose of these studies is to provide banks with benchmarking data to better understand the financial performance of commercial borrowers and prospects. In a typical year, at least eight of the ten largest U.S. commercial banks participate. Because RMA covers most of the biggest banks (plus several hundred regional banks) and the U.S. banking system is so concentrated, the dataset allows us to track the majority of commercial lending activity, reducing concerns that we are missing changes in certain borrower types over time. Appendix A provides additional detail on RMA's collection process and dataset.

RMA gathers financial statements collected by banks, and categorizes them according to statement type (unqualified audit, review, compilation, tax return or other), and the borrower's six-digit NAICS code, region (Northeast, Southeast, Central, South Central, North Central, or West), and size category (<$1 million, $1-$3 million, $3-5 million, $5-$10 million, $10-$25 million, or >$25 million of revenue).

RMA's categorization of the five statement types allows us to measure the extent to which banks rely upon unqualified audits, reviews, and compilations (collectively, AFS) in lending. We briefly discuss each of the AFS types. Unqualified audits provide positive assurance from an

[11] See https://www.rmahq.org/press-releases/2022/prominent-banking-executives-to-help-rma-members-meet-emerging-risk-challenges/?gmssopc=1

independent accountant that the financial statements are reported in accordance with Generally Accepted Accounting Principles (GAAP). Unqualified audits are accompanied by complete footnote disclosure, thus providing the most information and highest assurance level of all statement types. Reviews also include footnote disclosure but provide only negative assurance—an independent accountant performs analytical procedures and interviews management to assess whether the financial statements are misstated, but does not perform substantive procedures to obtain positive evidence of an account balance. Compilations provide no assurance about financial statement balances (and do not require footnote disclosure); an independent accountant merely organizes the firm's financial information in the form of GAAP financial statements. Thus, unqualified audits, reviews, and compilations represent AFS given the attestation provided by an independent accountant.[12]

We classify the two remaining statement types without CPA attestation—tax returns and other statements—as non-AFS. All U.S. firms are required to file a tax return with the IRS annually, which is prepared using a tax basis of accounting, and lacks footnotes and a cash flow statement.[13] The primary verification mechanism is corporate tax enforcement (e.g., Gallemore and Jacob 2020), rather than external assurance. (Although an independent CPA may prepare the tax return, they generally do not provide assurance around the numbers in the return nor is tax return preparation considered an "attestation" service).

"Other" statements include financial statements that do not fit into any of the aforementioned categories. The overwhelming majority are management-prepared reports lacking any attestation by a CPA. Unfortunately, RMA classifies one type of attestation report as "other":

[12] According to the AICPA, "Although a compilation is not an assurance engagement, it is an attest engagement" (AICPA 2016) because the CPA attests that the financial statements are in the form of GAAP financial statements. Approximate costs for these statement types reflect the amount of information and assurance provided. Badertscher et al. (2023) report that, for a firm with $5M-$10M of assets, unqualified audits cost $46,000, reviews cost $19,000, and compilations cost $7,000 (all annual figures).
[13] Firms with less than $250,000 in assets do not have to produce a balance sheet.

qualified audits in which an independent CPA provides an "except for" opinion stating that the financial statements follow GAAP except for certain aspects. Historically, RMA categorized qualified reports separately, but began consolidating them with "other" statements because they appeared so infrequently. RMA provided us with data from 2012 and 2017 confirming that qualified audits represent less than 3% of financial statements collected in both years, indicating growth in qualified audit opinions is immaterial and not driving the trend we identify. Information sources that are not in the form of a financial statement—for example, credit reports or loan officer notes (e.g., Campbell et al. 2019)—are not included in the dataset, as RMA's main purpose in assembling the data is to tabulate financial statement ratios by industry and borrower size, and provide this information to its bank members.[14] Given tax returns and other statements generally provide less information and no assurance, they are considered lower information quality statements for the purposes of bank screening and monitoring.

To illustrate the data, for a given bank, we observe the total number of financial statements collected from borrowers in the Northeast in NAICS 321920 (wood container and pallet manufacturing) with between $5 million and $10 million of revenue, in 2012, categorized by the type of statement collected. If a borrower provides more than one statement to the bank, RMA records the statement with the highest verification level. RMA publishes summary statistics from this data in its Annual Statement Studies and lists participating banks. Our sample covers nearly 3 million financial statements collected during 4,519 bank-years between 2002 and 2017 (we do not observe the statements themselves; just the aggregate figures by bank, statement type, industry, region, firm size category, and year). Appendix A provides additional detail on RMA's collection process and dataset.

[15] "Transforming commercial lending," PayNet, July 18, 2022. Accessed at https://paynet.com/about/

We supplement the RMA data with three additional data sources for the cross-sectional analyses in the second part of the paper. First, we develop a proxy for lenders' technology adoption using data from PayNet. Founded in 2001, PayNet is a commercial credit bureau focused on the U.S. equipment finance market. According to their website, their database contains $1.7 trillion of current and past obligations from 25 million lease and loan contracts, which they claim is the "largest proprietary database of small business loans, leases, and lines of credit in existence."[15] PayNet leverages modern information technology to collect borrower payment history and contract information directly from lenders' internal systems. It then verifies this data, combines it with external sources such as macroeconomic and trade data, and uses data analytics to develop credit scores, default probabilities, and credit reports that it sells to member lenders.[16] These products represented a major development in the SME lending market, as prior to PayNet lenders regularly originated contracts without knowing whether the borrower had previously serviced similar obligations. Over 20 lenders joined PayNet in the year following its 2001 launch, and we observe almost 200 more join by the end of our sample in 2014. Members include eight of the ten largest lenders in the market—a group that includes GE Capital, Bank of America, John Deere, Volvo, and Wells Fargo. PayNet data are used in Doblas-Madrid and Minetti (2013), Chen, Hanson, and Stein (2017), Sutherland (2018), and Darmouni and Sutherland (2021), and are the source of the Equifax Small Business Lending Index commonly referenced in the press.

PayNet does not share its full dataset with researchers, but was willing to provide a panel of 20,000 randomly chosen borrowers' credit files, spanning 1998 to 2014. This panel allows us to observe every contract the borrower ever had during the sample period with a PayNet lender, regardless of when the lender joined PayNet. The credit files detail over 400,000 contracts of these

[16] Lenders become PayNet members by agreeing to share all of their equipment finance credit files (like other bureaus, PayNet operates on the principle of reciprocity).

borrowers with any lender who has ever joined PayNet, totaling nearly six million contract-quarter observations. We do not observe lender or borrower identities, just an anonymous identifier.

Second, we obtain a sample of public liens on business property, also known as "UCC filings" or "UCC-1 filings" (secured credit transactions are governed under Article 9 of the Uniform Commercial Code), from all 50 U.S. states. Lenders make UCC filings with the borrower's Secretary of State to establish ex-ante claim to collateral that the borrower pledges to obtain financing. Filings specify the borrower, lender, and details about the collateral (e.g., the make, model, year, serial number, and features of a piece of equipment such as its horsepower or condition) to ensure correct identification in the event of default or dispute. Lenders face strong incentives to make UCC filings for secured contracts.[17] Doing so establishes their priority in the event of bankruptcy, and the cost of filing is small (typically $25 or less). Figure 2 provides an example UCC filing.

Randall-Reilly, a data vendor focused on the equipment finance sector, has compiled a comprehensive dataset (Equipment Data Associates data, or "EDA" data) based on UCC filings dating back to the 1990s. From each UCC filing, they extract all borrower, lender, and collateral information, and combine it with additional borrower data from DNB and other datasets. They also assign each piece of collateral to one of 497 equipment codes (the primary categories they cover include agriculture, construction, office, lift trucks, logging, machine tools, medical, trucking, and woodworking). Filings occasionally contain an equipment value; when this is missing, Randall-Reilly appends an estimated value based on list prices, auction values, trade publications, and survey information. At the county-year level, the correlation between the total number of filings and dollar value of equipment financed is 0.97 (Gopal and Schnabl 2022).

[17] Lenders commonly make UCC filings for leases, even though they retain ownership of the asset, because courts often recharacterize operating leases as capital leases in bankruptcy (Contino 1996; Gopal and Schnabl 2022).

Randall-Reilly also cleans and standardizes borrower and lender names, and the manufacturer, model, and year of each piece of equipment to facilitate analysis.

Randall-Reilly's primary business is selling data to over 4,400 equipment manufacturers and lenders, who use it to guide their marketing efforts and identify industry trends. Randall-Reilly has several hundred employees focused on extracting, cleaning, and augmenting data from UCC filings. UCC filing data similar to ours (from EDA or competing vendors) has been used in Edgerton (2012), Thakor (2018), Murfin and Pratt (2019), Gopal (2021), Ma, Murfin, and Pratt (2022), Gopal and Schnabl (2022), and Darmouni and Sutherland (2023).

Third, we collect CPA firm license data from websites populated by State Boards of Accountancy (see also Vetter 2022 and Sutherland, Uckert, and Vetter 2023). Each license details the name, address, and the license number, state, issuance date, and expiration date. Because parts of our estimation rely on identifying stocks and flows of CPA firms, we drop licenses from states that do not consistently report information about expired licenses.[18] Our license data cover over 50,000 unique CPA firms in over 2,000 counties between 1997 and 2019.

3.2 Summary Statistics

Table 2 presents summary statistics. In Panel A, we describe the financial statement data from RMA. Of the nearly 3 million borrower financial statements collected by banks in the dataset, 47% are AFS: 22% are unqualified audits, 12% are reviews, and 13% are compilations. The average (median) number of statements collected within the bank-industry-region-year unit of observation is 11 (2). Based on RMA's size categories, 16% of statements come from firms with less than $1 million of annual revenue, 16% from firms with $1-$3 million, 9% with $3-5 million, 13% with $5-$10 million, 16% with $10-$25 million, and 31% with over $25 million.

[18] We drop CPA firm licenses from the following 21 states: Alabama, Arizona, Hawaii, Idaho, Indiana, Kansas, Kentucky, Maine, Minnesota, Nebraska, North Dakota, Ohio, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Utah, West Virginia, Wisconsin, and Wyoming.

Panel B describes the EDA and PayNet data. We identify banks and nonbanks based on the EDA lender name field using the algorithms in Erel and Liebersohn (2020), Chernenko and Scharfstein (2022), Gopal and Schnabl (2022), and Howell et al. (2022) and eliminate filings where the lender cannot be assigned.[19] Our balanced panel of merged UCC filing and CPA firm data contains 43,470 county-year observations. For the average county-year, there are 32 UCC filings for banks and 73 for nonbanks. Based on EDA's estimated equipment values, this represents $3.79 million of equipment financed by banks and $6.68 million by nonbanks. In the average (median) county, there are 20.1 (two) CPA firms. Twenty-nine percent of counties are CPA deserts, defined as counties with zero CPA firms.

As for the PayNet variables measured at the industry-state-year level, on average about 80% of originations are by a PayNet member, though there is considerable time series and cross-sectional heterogeneity.[20] Over 200 lenders join in a staggered pattern between 2001 and 2014. Moreover, many lenders specialize by collateral type, industry, and location. For example, one quarter a national agricultural equipment captive might join, followed by a diversified regional bank the next quarter, followed by an auto captive and large national bank the subsequent quarter. Thus, while the bureau and its information coverage grow over time, the growth is sporadic and market- and location-specific. Consistent with this, Figure 3 illustrates how the growth in the number of bureau contracts varies across collateral markets over time.

3.3 Two Stylized Facts

Before detailing our empirical analysis, we discuss two stylized facts motivating our investigation of technological advances and credit market structure changes as potential drivers of the AFS decline shown in Figure 1.

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[19] Thus, our dataset does not include IRS claims.

[20] By construction, in early years there are fewer lenders participating. *Tech Adoption Rate* is low, but grows as more lenders join and share information.

3.3.1 "Financial Statements not Required"

Figure 4 presents excerpts from advertisements by PayNet. PayNet advertises their credit score and credit rating products using the slogan "Financial statements not required." Their advertisements elaborate: "PayNet reduces your lending risk by providing an absolute measure of credit risk at both the borrower and portfolio level *on millions of small businesses for which financial statements are not available*" (emphasis added).[21] Figure 5 presents a collage of advertisements of other credit data vendors (Rutter, Enigma, and Tax Status) (see ELFF 2023 for a more comprehensive overview). The advertisements discuss various ways these vendors help lenders obtain alternative data or financial statement components (rather than complete, externally verified financial statements) to aid their screening and monitoring. For example, Rutter (and a number of other vendors whose products we reviewed) helps lenders access digital payment data from commerce (e.g., Amazon), payment (Stripe), and accounting systems (Quickbooks).[22]

Supporting this, Figure 6 presents responses to the 10th annual Credit Managers Survey, conducted by the Equipment Lease and Finance Association (ELFA 2021), the trade association representing the equipment finance sector. The survey asked 211 equipment finance credit managers about their credit processes, regulatory burdens, and macroeconomic and technological trends. Our focus is on the "Credit Scoring Threshold"—the loan size that credit managers report being authorized to approve based on credit scores alone (i.e., no other information collection is required—financial statements or otherwise). Panel A reports that in 2017, just 5% (40%) of respondents report a credit scoring threshold of over $750,000 ($150,000) whereas in 2021 the

[21] One former lending executive we spoke to reacted to Figure 1 by saying "I think it's a function of growing sophistication of both lenders and fraudsters, as well as a desire for automation and speed (and reduced cost) – obtaining financial statements is a manual time-consuming slow process, and new instantaneous, objective/accurate ways of obtaining information are growing."

[22] Bank Director's 2022 Technology Survey reports that most banks rely on APIs which link into a borrower's general ledger or payment system, and that a large majority of banks plan to increase their technology spending.

percent jumps to 10% (50%). One respondent explained, “As we gather more data to support our scoring model… raising the scorecard threshold might become necessary” (ELFA 2021). Panel B shows that a majority of respondents report approving loans within their firm’s credit scoring threshold in one day or less—a timeframe that is difficult to achieve with a standard AFS request and review by a credit manager.

The role for technology has also grown in compliance and bank supervision. U.S. banks face oversight from the Federal Deposit Insurance Corporation, Federal Reserve System, and Office of the Comptroller of the Currency. Credit standards are a considerable focus of this oversight: banks must demonstrate they have developed and are enforcing written policies and procedures related to measuring and controlling credit risk (OCC 2014, 2020). Collecting financial statements and other information from borrowers aids banks’ compliance efforts. As Basel (2000) explains:

> The credit files should include all of the information necessary to ascertain the current financial condition of the borrower or counterparty as well as sufficient information to track the decisions made and the history of the credit. *For example, the credit files should include current financial statements*, financial analyses and internal rating documentation, internal memoranda, reference letters, and appraisals (emphasis added).

While this 2000 guidance emphasizes financial statements and other specific formal documentation, more recent directives indicate that regulators are open to evaluating a range of technology-based tools in their credit risk review. Interagency guidance from the Federal Deposit Insurance Corporation, Federal Reserve System, Office of the Comptroller of the Currency, and National Credit Union Administration in 2020 states:

> The agencies believe institutions have significant flexibility to use various types of technology to assist in the credit risk review process; as such, the agencies decline to recommend the use of any specific types of technology. (Interagency Guidance on Credit Risk Review Systems 2020).

Hence, lenders, software vendors, and regulators all point to ways in which technology can substitute for AFS in screening and monitoring.

3.3.2 Nonbank Lender Growth

Several recent studies document the rise of nonbank lenders, and trace this growth to banks cutting lending during the crisis, banks facing more regulatory oversight, and technological advances that obviate the need for branch-based lending (Chernenko et al. 2022; Gopal and Schnabl 2022; Loumioti 2022). In Figure 7, we plot bank and nonbank originations between 1997 and 2019. Banks and nonbanks had a similar number of UCC filings in 1997, but thereafter the nonbank filings grow more quickly. Like Gopal and Schnabl, we find a steeper drop for bank than nonbank originations during the crisis, and that nonbanks continue to grow their market share after.

4 Aggregate Evidence on Banks' Financial Statement Collection

Our first set of analyses track banks' collection of AFS from borrowers over the 2002-2017 period. Specifically, we track financial statement collection using a ratio. For the AFS ratio, the numerator is the sum of unqualified audits, reviews, and compilations. For the individual component ratios, the numerator is simply the number of unqualified audits, reviews, or compilations as labeled. The denominator for all ratios is the total number of statements collected by banks, including AFS, plus tax returns and the "other" statement category. Hence by construction, all of our observations condition on some level of financial report collection, and our analyses examine the extent of CPA involvement.

In Figure 8, Panel A (B, C, D) we regress the proportion of statements that are AFS (unqualified audits, reviews, compilations) on year fixed effects, and various controls and fixed effects as described below. The unit of observation in the regressions is bank-industry-region-year (industries are at the three-digit NAICS level), and the regressions are weighted by the number of statements collected within this unit of observation. As a baseline, the dark blue line in Panel A of Figure 8 reproduces Figure 1, showing a reduction in AFS from 57% in 2002 to 33% in 2002.

Then, to evaluate the possibility that this downward trend simply stems from changes in the types of borrowers or banks in the RMA data, we plot four additional lines in each panel, corresponding to the year fixed effects of regressions that have added borrower or bank characteristics to the baseline regression. First, the red line plots the year fixed effects from a regression of either AFS, unqualified audit, review, or compilation rates on year, industry, and region fixed effects. Industries differ in their accounting rules and the preponderance of AFS in lending, and regions differ in their mix of industries and the nature of the banking market and economy. Therefore, sample composition changes with respect to borrower industry or location could generate a trend in statement collection between 2002 and 2017. However, in all four panels, the red line is virtually indistinguishable from the dark blue line which included only year fixed effects, indicating that changes in sector or geographic representation have little to do with the downward trend.

Second, we add controls for average borrower size. Larger firms are more likely to obtain AFS (Lisowsky and Minnis 2020), and changes in the size of borrowers covered by RMA could generate their own trend. However, the green line for all four panels shows a highly similar decline to the dark blue line. Third, banks differ in their size and specialization, and these features link to their AFS collection (Berger et al. 2017). The orange line adds bank fixed effects and finds a slightly less stark, though still notable, decline (AFS declines from 53% to 35%, unqualified audits from 21% to 16%, reviews from 16% to 10%, and compilations from 17% to 9%). Adding time-varying controls for bank fundamentals (e.g., size, profitability, growth, loan loss provisions, capitalization, and exposure types) does not alter our inferences.

Because borrower size and industry explain a large portion of AFS collection variation, it seems unlikely that that the trend simply stems from changes in the types of borrowers in the sample. However, we cannot be certain because our dataset does not allow us to track individual borrowers or lending relationships, so we conduct additional analyses to validate this assumption. RMA Annual Statement Studies report average financial ratios for borrowers in each industry-region-size category. We use these ratios to control for the debt-to-equity ratio, pre-tax profit margin, and intangible assets-to-total assets measured as the average at the industry-region-year level (the most granular level available to us). Panel A of Appendix B shows that the trend changes little, and moreover, adding these fundamental variables increases the R-squared by only 0.001. Additionally, Panel B shows that the decline is not solely in industries with more patenting (e.g., computers & electronics, chemicals, and information). Combined, this suggests that trends in the use of intangibles as collateral alone (e.g., Loumioti 2012) do not explain the AFS decline.

Additionally, we plot AFS by borrower size category. If the trend was driven by turnover unobservable to us (e.g., the regular churn of new and failing firms), then the results should be concentrated in the smallest borrower group (<$1 million of revenue) as much larger borrowers tend to be established firms and not startups. A separate concern is that IPOs or private equity acquisitions typically involving larger firms somehow explains the trend. However, Panel C of Appendix B does not find any evidence supporting either alternative explanation, as we find less AFS collection over time in all borrower size categories.

Third, we consider the possibility that the trend stems from changes in the set of banks voluntarily participating in RMA's annual statement studies. Specifically, we limit the sample to banks participating every single year between 2002 and 2017, and continue to include bank fixed effects. The light blue line in Figure 8 shows a marked decline that is comparable to our baseline result (though the starting and end points of this plot are lower, likely due to us losing nearly 70%

of our sample and studying a specific subset of banks meeting the constant participation requirement). Further, Panel D of Appendix B shows an AFS decline for both the largest (top 10 by statement collection) and remaining banks, though the decline occurs earlier for the largest banks. In sum, Figure 8 provides little indication that changes in borrower or bank composition are driving the decline in AFS or unqualified audit collection.

As a final robustness check to ensure our findings are not simply a manifestation of RMA's data collection practices or some other mechanical explanation, we conduct a placebo test comparing governments and schools (two-digit NAICS codes 61 and 92) to other industries. The idea underlying this test is that the financial reports from governments and schools would be exposed to the same data collection practices as other sectors, but because most governments and schools face reporting mandates (Cuny et al. 2021; Duguay 2022), their use of AFS should not be responsive to changes in the marketplace for financial reporting.[23] In other words, if we identify a similar AFS decline in governments and schools as other sectors, we would be concerned that our findings are the result of data collection or measurement issues and not changes in the cost-effectiveness of AFS.

Figure 9 shows little AFS decline for governments and schools (from 90% in 2002 to 84% in 2017) versus a major decline for other sectors (63% to 46%). This pattern lends credibility to our hypothesis that marketplace developments could be behind the decline in AFS collection, because borrowers with the most elastic AFS supply experience the sharpest decline. Additionally, the pattern does not support mechanical explanations based on measurement, such as inflation or data collection changes, as these explanations should affect both subsamples.[24] Finally, if a single

[23] To focus on this elasticity, we limit the sample to borrowers with at least $25 million of revenue (such that most governments and schools begin with AFS).
[24] As an additional step, we eliminate banks whose year-over-year statement count growth ever exceeds 25%, in case such instances reflect M&A or changes in information sharing with RMA. We find a similar AFS decline.

event (e.g., change in accounting standards or regulation) on its own explained the trend, we would expect a one-time AFS decline rather than the gradual one we observe.

To this point, we have shown a stark decline in the proportion of AFS collected by banks, and that this pattern is not explained by sample composition changes, measurement issues, or single events. The remainder of the paper focuses on two specific marketplace developments that we hypothesize explain at least part of the ongoing decline: technology adoption and nonbank lending competition.

5 Technology Adoption

5.1.1 Research Design and Results

We examine technology adoption and AFS collection using the following specification:

$$y_{ist} = \alpha_{it} + \alpha_s + Tech\ Adoption\ Rate_{ist} + \ Size_{ist}\ +\ \varepsilon_{ist}.\ (1)$$

The unit of observation is industry-state-year, where *i* indexes industries based on three-digit NAICS codes, *s* indexes states, and *t* indexes years. The regressions are weighted by the number of statements collected within this unit of observation. The dependent variable is *AFS* or *Unqualified,* the proportion of statements collected by banks that industry-state-year that are AFS or unqualified audits. We control for industry-year fixed effects (α_{it}) and state fixed effects (α_s) to abstract away from differences in reporting practices across sectors and locations, time-varying economic conditions in each industry, and overall accounting and audit standards. *Tech Adoption Rate* is the proportion of contracts originated that industry-state-year by lender members of PayNet. Intuitively, this variable captures technology adoption in a market by measuring the extent of lending based on information sharing technology. Variation in this variable comes from a) lenders joining PayNet in a staggered pattern, and b) lender specialization. Thus, as shown in Figure 3 the bureau's information coverage evolves not in a linear pattern (as with common technology growth), but an uneven pattern given lenders with different specialization join each quarter. *Size* measures the log average borrower sales that industry-state-year. We double cluster standard errors by industry and state. The sample is limited to banks operating in only one RMA region (the Northeast, Southeast, Central, South Central, North Central, or West) such that we can reasonably trace statement collection within an industry-state to the extent of information sharing in the industry-state.[25]

The objective of these tests is to document a substitute relation between AFS and the credit reports and scores provided by credit bureaus. Thus, although our setup resembles a difference-in-differences specification, we do not view *Tech Adoption Rate* as exogenous—by construction it captures the extent of voluntary participation in PayNet, including by lenders seeking to reduce their screening and monitoring costs. In light of this, we interpret our results with caution and evaluate potential validity threats below.

Table 3 presents the results, with Panel A focusing on AFS and Panel B focusing on unqualified audits. Column 1 of both panels shows a negative and significant coefficient on *Tech Adoption Rate*, consistent with less AFS collection as more lenders access alternative information provided by the bureau.

Of course, lenders do not randomly decide to join PayNet. Liberti et al. (2022) investigate lenders' motives for joining PayNet, and find that early joiners tend to be large and less specialized. Intuitively, larger lenders rely more on hard information (Stein 2002) such as credit reports and scores provided by the bureau, and less specialized lenders sacrifice little proprietary information when sharing their credit files. Lenders also use credit report information to help them expand into new markets. He et al. (2022) examine bank technology adoption from the perspective of communications tools and software, and likewise find a distinct bank size pattern. Then, one concern is that unobservable economic shocks affect lenders differently according to their business

[25] Unfortunately, the RMA does not provide more granular regional detail.

model (e.g., their size or portfolio exposure), and this manifests in different AFS collection patterns for reasons unrelated to technology adoption.

To address this, we classify each industry-state-year observation according to its typical lender size tercile, collateral specialization (the average lender is exposed to eight or fewer collateral types), and industry specialization (the average lender deals with 50 or fewer three-digit industries). We then interact each of these indicators with year fixed effects, such that our specification flexibly controls for how the economy differentially affects lenders of various size and portfolio focus. Column 2 continues to find a significantly negative coefficient on *Tech Adoption Rate* for both AFS and unqualified audits.

Another concern is that our column 1 results are merely picking up pre-existing trends. In column 3, we add lagged versions of *Tech Adoption Rate*, which should load negatively under such an explanation. However, we find the lagged variables are insignificantly positive, and moreover, the contemporaneous *Tech Adoption Rate* variable remains significantly negative. Last, in column 4 we conduct a placebo test where we measure *Placebo Tech Adoption Rate* based on a randomly chosen other industry in the same state. If our column 1 results stem from common technology trends rather than industry-specific information, or from local economic shocks, then this placebo variable should be significantly negative. Column 4 shows that it is not.

Overall, our evidence is most consistent with technology adoption creating new information sources that substitute for AFS. To gauge the economic significance of our results, recall from Figure 1 that AFS collection declined from 57% in 2002 to 36% in 2014, the end of our PayNet sample. For unqualified audits, the collection rate falls from 23% to 17%. During the same period, *Tech Adoption Rate* grows by almost one unit, and therefore the -2.1% (-1.1%) weighted least squares coefficient from column 2 in Panel A for AFS (Panel B for unqualified audits) corresponds to over one-tenth of the AFS and unqualified collection decline.[26] Thus, the expansion of PayNet is associated with a nontrivial decline in AFS collection during our sample window. Of course, ample AFS variation remains unexplained, and PayNet constitutes just one of many technological tools emerging during this period (see Figure 5 or ELFF 2023). Additionally, other developments beyond technological advances can explain part of the AFS decline, including nonbank lending which we explore in our next section.

5.2 Nonbank Lending

5.2.1 Research Design and Results

Next, we study bank and nonbank lending using the EDA data. We model originations using the following specification:

$$y_{cjt} = \alpha_{cj} + \alpha_{jt} + Log\ CPA\ Firms_{ct}\ x\ Bank_j + Log\ CPA\ Firms_{ct}\ x\ Nonbank_j\ +\ \varepsilon_{cjt}. \quad (2)$$

The unit of observation is county-lender type-year, where c indexes counties, j indexes lender type (bank or nonbank), and t indexes years. The dependent variable is *Log Filings*, one plus the log number of UCC filings[27], or *Log Value*, the log dollar value of equipment securing the contract as estimated by EDA.[28]

We control for county-lender type fixed effects (α_{cj}) to account for time-invariant factors affecting bank and nonbank lending in each county, including the industry base and geography. We control for lender type-year fixed effects (α_{jt}) to account for the overall state of the economy and how it affects lender types differently. *Log CPA Firms* is the log number of unique CPA firms licensed in the county that year. We cluster standard errors by county.

[26] By construction, *Tech Adoption Rate* is zero when the bureau launches in 2001, and by the end of our sample, all lenders are members and *Tech Adoption Rate* is 100%.
[27] Counties with zero filings are rare. Nevertheless, we confirm our inferences are the same using a Poisson specification (e.g., Cohn, Liu, and Wardlaw 2022).
[28] Actual prices are provided for under 10% of the UCC filings. For most of the remaining filings, EDA appends a value estimate based on its database of list prices, auctions, trade publications, and survey information.

Intuitively, we seek to understand whether banks rely less than nonbanks on CPA services, and how this reliance is changing as nonbank share has grown. Although related work examining nonbank growth uses changes in bank regulation or supervision for identification, our research question precludes this approach because such changes directly affect bank lending standards—the exclusion restriction is violated. Instead, our strategy is to study changes in local CPA supply, and measure changes in bank lending using nonbank lending as a benchmark to control for local economic conditions and credit demand. Our assumption is that if AFS are more important to banks given their screening and monitoring approach, then bank credit should change more than nonbank credit when CPA supply shifts. By examining lending changes within a county-year, we are able to abstract away from the broader determinants of nonbank lender growth (e.g., regulation and overall economic conditions) and isolate bank versus nonbank reliance on CPA services.

Table 4 presents the results of estimating equation (2). In terms of the number of originations, column 1 shows that bank lending is nearly twice as sensitive as nonbank lending to CPA supply, and the difference is statistically significant at the 1% level. (With our interacted fixed effect structure, note that the coefficients for *Log CPA Firms* x *Bank* and *Log CPA Firms* x *Nonbank* are identical to those one would obtain from separately estimating equation (2) for banks and nonbanks.) Economically, a within-county standard deviation change in the CPA supply is associated with 18% of a within-county standard deviation change in bank originations; for nonbank originations the figure is just 9%. Thus, our estimates suggest that bank lending is twice as sensitive as nonbank lending to CPA supply.[29] Column 2 adds county-year fixed effects, such that we compare the lending change for banks and nonbanks within the same location and time period. Our inferences are similar. Columns 3 and 4 repeat these tests using *Log Value* as the

[29] The components of this calculation are as follows: a) the average within-county standard deviation of *Log CPA Firms* is 0.30, b) the average within-county standard deviation of bank (nonbank) originations is 0.58 (0.69), and c) the column 1 coefficient for *Log CPA Firms* x *Bank* (*Log CPA Firms x Nonbank*) is 0.348 (0.197). Then, a x c / b = 18% (9%) for banks (nonbanks).

dependent variable. Again, we find far greater lending sensitivity to CPA supply for banks than nonbanks. Using a within county-year estimation in column 4 produces similar inferences.

5.2.2 Robustness

Table 5 provides robustness analyses for these results. For parsimony, we focus on column 2 of Table 4, containing our strictest (within county-year) estimation.

First, we measure CPA supply using census data rather than CPA firm license data. Although the license data specifically tracks registered CPA firms separately from related firms (e.g., bookkeeping services and tax preparation firms), one limitation of the license data is that it only provides current addresses, which introduces measurement error for historical county assignments. Column 1 shows our results are unaffected.

Second, we develop a CPA supply measure designed to capture more drastic changes in the availability of CPA services. Specifically, we identify counties that have zero CPA firms, or "CPA deserts" (similar to banking deserts or food deserts in related literatures). Our inclusion of county-year fixed effects means that our estimation using this measure effectively analyzes what happens to originations when a county becomes or emerges from being a CPA desert. Column 2 finds a similar pattern of results to Table 4: bank lending is far more sensitive than nonbank lending to CPA supply changes. Figure 10 studies lending in event time in the four years surrounding a county becoming a CPA desert. In the pre-desert period, bank and nonbank lending evolve similarly (the confidence bands overlap). After the county becomes a desert, bank lending significantly declines, and nonbank lending slightly increases, consistent with banks relying more than nonbanks on CPA services.

Third, banks and nonbanks may respond differently to economic conditions, even within the same county. As one example, Gopal and Schnabl (2022) find nonbanks filled much of the void created by bank lending decreasing following the financial crisis. Then, if CPA supply reductions are driven by a deterioration in economic conditions, for example, the bank and nonbank differential lending pattern we document may be spurious. Although equation (2) controls for lender type x year fixed effects, this may not adequately account for geographic variation in the business cycle. To address this, we augment equation (2) with state x lender type x year fixed effects, which more flexibly and robustly account for how different lenders respond to local economic conditions. Column 3 shows our results are slightly stronger than in Table 4.

Overall, our findings are best explained by banks and nonbanks having different sensitivity to CPA supply, and not our choice of CPA supply measures or how banks and nonbanks respond to economic conditions.

5.2.3 Evidence from the Time Series and Nonbank Growth

Next, we investigate how the sensitivity of lending to CPA supply changes over time. Specifically, we divide our 2000-2019 sample period into four equal-length periods (2000-2004, 2005-2009, 2010-2014, and 2015-2019) and re-estimate equation (2) on each. Given our Figure 1 evidence, our main focus is on banks' sensitivity to CPA supply, but we report results for nonbanks as well.

Table 6 presents the results, with Panel A studying filings and Panel B studying the value of equipment financed. Panel A shows that the coefficient on *Log CPA Firms x Bank* declines by more than two-thirds over the two-decade period, from 0.709 in 2000-2004 (column 1) to 0.194 in 2014-2019 (column 4). The column 1 to 4 decline is statistically significant at the 1% level. The interaction term for nonbanks also significantly declines over this period. Panel B shows a similar pattern for the value of equipment financed. Interestingly, by the 2015-2019 period, bank sensitivity to CPA supply roughly matches the nonbank sensitivity from ten years prior, suggestive of banks evolving to rely less on AFS in response to growing nonbank competition.

To test this interpretation more directly, Table 7 examines what happens when nonbanks expand more in a given county. Specifically, we study how bank sensitivity to CPA supply changes once the county experiences large growth in nonbank lending. Intuitively, nonbank expansion increases the competitive pressure on banks to soften AFS requirements, and by extension, bank sensitivity to CPA supply. To test this, we limit the sample to banks, and measure the change in bank lending as a function of the change in CPA supply, an indicator for counties with high nonbank lending growth, and the interaction between these two factors. Our indicator for high nonbank lending growth during each of the prior two years is based on various thresholds (e.g., 10%, 15%, etc.) as shown in the bottom of the table.[30] We find a negative interaction term in all columns that is statistically significant in most, consistent with nonbank expansion compelling banks to reduce reliance on AFS.

Thus, the overall trend is that banks increasingly behave more like nonbanks in terms of their sensitivity of lending to CPA supply, and both banks and nonbank lending has become less responsive to CPA supply changes.

6 Making Sense of the AFS Decline: 'Race to the Bottom' or Cost Effective?

Our final tests examine the consequences of the AFS decline. One possibility is that defaults and bank losses rise, to the extent that the decline is a symptom of competition compelling banks to cut lending standards in a so-called 'race-to-the-bottom.' An alternative is that the AFS decline simply results from banks trading off information sources (e.g., Petersen and Rajan 2002), and AFS falling out of favor as technology produces cheaper and more timely forms of credit information. Then, we would not expect any relation between AFS collection and bank performance.

To investigate this, we collect bank performance information from bank Consolidated Reports of Condition and Income (Call Reports), and measure profitability (return on equity [ROE] and return on assets [ROA]) and commercial and industrial ("C&I") loan chargeoffs (C&I loans /

[30] Using alternative approaches (e.g., measuring average growth in recent years) yields similar inferences.

lagged C&I loans). Table 8 presents regressions modeling C&I chargeoffs and bank ROA as a function of lagged AFS collection and lagged controls for bank size, residential loan exposure, commercial real estate exposure, agricultural loan exposure, household loan exposure, trading assets, deposits, capitalization, and loan growth, all winsorized at the 1% and 99% level. We also include bank and year fixed effects.

Panel A studies chargeoffs. Columns 1 finds that, if anything, AFS reductions are associated with fewer chargeoffs (AFS_{t-1} is positive and almost significant). To ensure that this is not merely driven by the inclusion of the crisis and early recovery years, column 2 eliminates observations from 2007-2010, and column 3 includes interactions between a 2007-2010 indicator and our control variables. In both cases, we continue to find a positive and significant coefficient for AFS_{t-1}, though some control variables change sign or significance. In columns 4-6, the coefficient of interest is Unq_{t-1}, and our inferences around financial statement collection and chargeoffs are the same. Likewise, Panel B repeats these tests using *ROA* as the dependent variable, and once again finds null results.[31] Overall, our evidence here is most consistent with banks substituting AFS for cheaper, more timely information sources.

7 Conclusion

Private firms in the U.S. face no reporting mandate, and their decision to engage a CPA firm is often a function of their lending relationships. Using a sample of nearly 3 million borrower financial statements collected by banks since 2002, we document a striking trend: banks are significantly less likely to collect AFS as part of their screening and monitoring efforts. In 2002, 57% of financial reports provided to banks were AFS, and this rate nearly monotonically declines to just 33% in 2017. For unqualified audits, the rate declines from 23% to 16% over the same period. These declines do not appear to be driven by composition changes, because we find a

[31] Our inferences are robust to a changes specification and to using alternative crisis and recovery period windows.

similar pattern after controlling for borrower characteristics (industry, location, and size) and bank fixed effects, and limiting the sample to banks sharing data with RMA every year.

We investigate two recent lending market developments for their potential to contribute to the trend. First, technological advances in information sharing, digitization, and data analytics have provided lenders with new alternative information sources that can substitute for AFS. PayNet, a large U.S. credit bureau, advertises itself using the slogan "Financial statements not required" and we trace its evolution to reduced AFS collection. Second, nonbank lender market share has grown considerably over the past two decades, and for regulatory and business model reasons, these lenders rely less on AFS in screening and monitoring. As nonbank market share has grown, bank lending has become less sensitive to CPA supply, consistent with banks adjusting their reporting requirements in response to nonbank competition. We find no indication that the overall AFS decline stems from banks cutting lending standards in a "race to the bottom." Instead our results are best explained by AFS becoming less efficient for screening and monitoring.

Overall, we document a stark trend in AFS collection that poses significant questions for the literature, accounting practice, and standard setters. While our focus limits our analysis to two plausible drivers of the trend, there are undoubtedly others at play. For example, technology has transformed credit origination in ways beyond the credit scoring innovations we study (e.g., He et al. 2021). Moreover, the market for CPA services has faced changes in both audit regulation and accounting standards for private firms (see Financial Accounting Foundation 2011 for a discussion). We encourage future research to investigate the role that these developments and others have played in the AFS decline.

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Overview of Empirical Analyses

Below we list the data sources and unit of observation for each of our main figures and tables in our empirical analyses.

Figure / Table	**Data source**	**Unit of observation**
Figure 1	RMA	Year
Figure 3	PayNet	Collateral type x year
Figure 7	EDA	Lender type x year
Figure 8	RMA	Bank x industry x region x year
Figure 9	RMA	Bank x industry x region x year
Figure 10	EDA	County x lender type x year
Figure 11	Federal Reserve	Year
Table 3	RMA, PayNet	Industry x state x year
Table 4	EDA, CPA license	County x lender type x year
Table 5	EDA, CPA license	County x lender type x year
Table 6	EDA, CPA license	County x lender type x year
Table 7	EDA, CPA license	County x lender type x year
Table 8	Call Reports, RMA	Bank x year
Appendix B, Panel A	RMA	Bank x industry x region x year
Appendix B, Panel B	RMA	Bank x industry x region x year
Appendix B, Panel C	RMA	Bank x industry x region x year x size category
Appendix B, Panel D	RMA	Bank x industry x region x year

Figure 1: Banks' Attested Financial Statement Collection

This figure plots banks' yearly average AFS collection rates between 2002 and 2017.

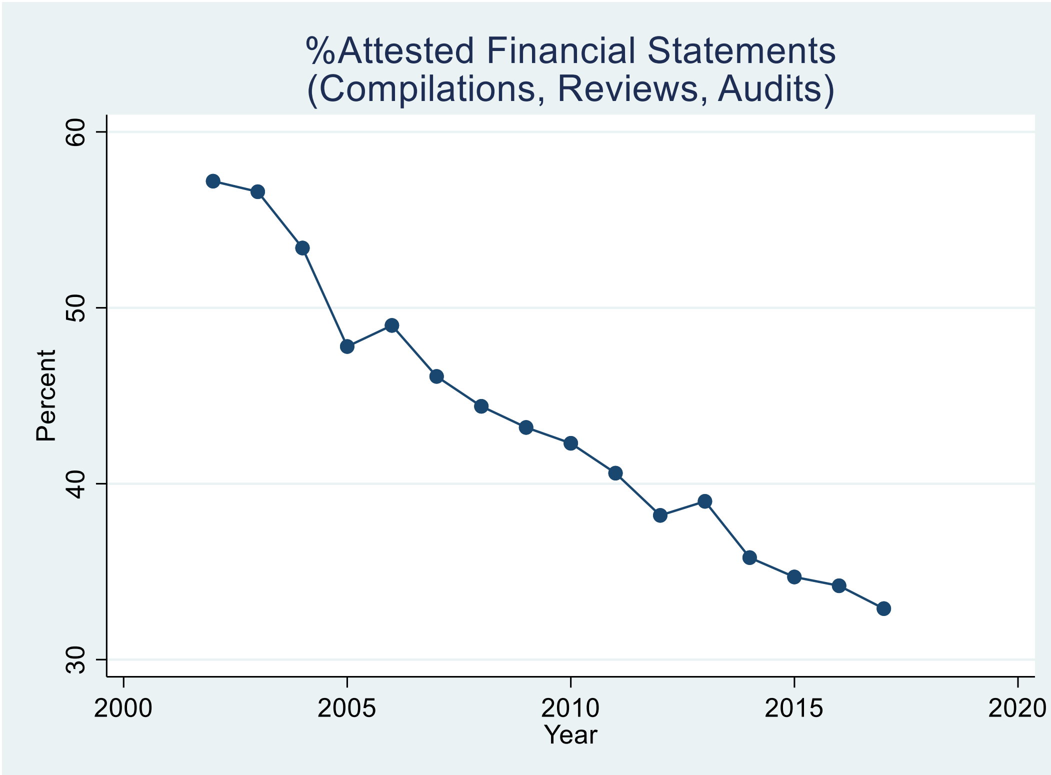


Figure 2: Example UCC Filing

The figure below provides an example UCC filing. The filing documents a loan for a forklift from Toyota Industries Commercial Finance, Inc. The forklift is a Toyota Model # 7FBEU18, and the serial number is #21898.

UCC-1 Form

FILER INFORMATION

Full name: **LIEN SOLUTIONS**

Email Contact at Filer: **UCCFILINGRETURN@WOLTERSKLUWER.COM**

SEND ACKNOWLEDGEMENT TO

Contact name: **LIEN SOLUTIONS**

Mailing Address: **P.O. BOX 29071**

City, State Zip Country: **GLENDALE, CA 91209-9071 USA**

DEBTOR INFORMATION

Org. Name: **SHAWMUT CORPORATION**

Mailing Address: **208 MANLEY ST**

City, State Zip Country: **WEST BRIDGEWATER, MA 02379-1044 USA**

SECURED PARTY INFORMATION

Org. Name: **TOYOTA INDUSTRIES COMMERCIAL FINANCE, INC.**

Mailing Address: **P.O. BOX 9050**

City, State Zip Country: **DALLAS, TX 75019-9050 USA**

TRANSACTION TYPE: STANDARD
ALTERNATIVE DESIGNATION:
CUSTOMER REFERENCE: MA-0-67035011-56034684

COLLATERAL

ONE (1) TOYOTA FORKLIFT MODEL # 7FBEU18 SERIAL # 21898

Figure 3: PayNet Coverage Variation

This figure plots the growth in PayNet information coverage for the five most common collateral types in our sample. Each series measures the growth in the number of open contracts in the bureau that year as a percentage of the maximum all time open contracts in the bureau for the collateral type.

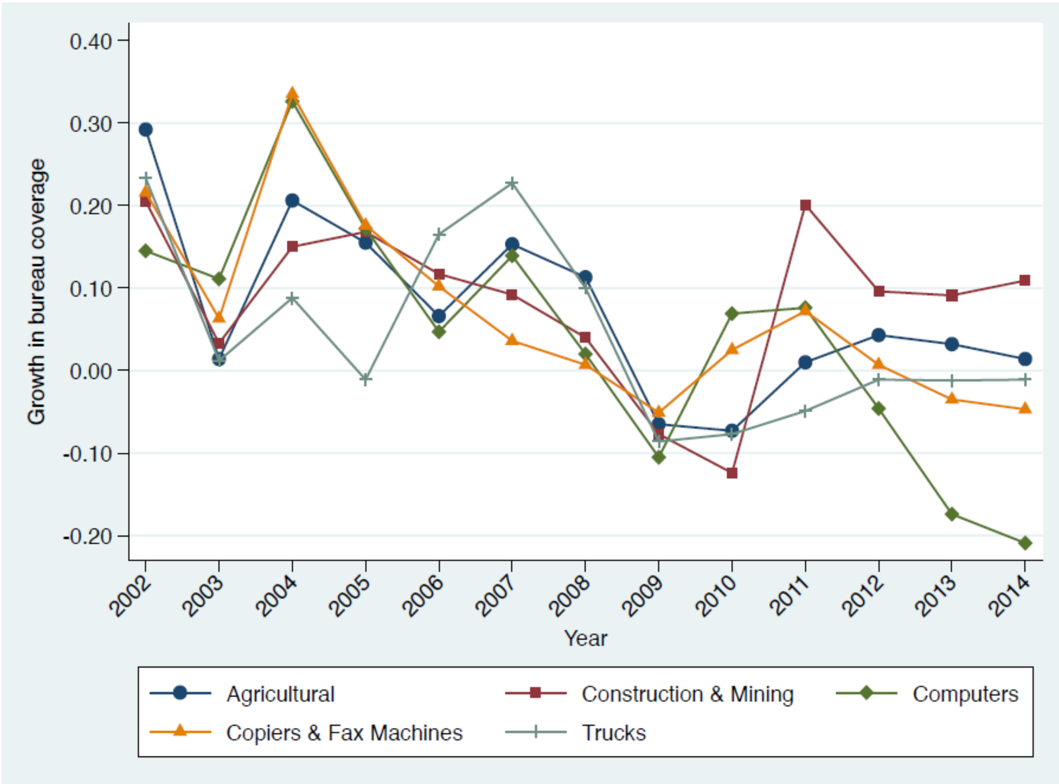
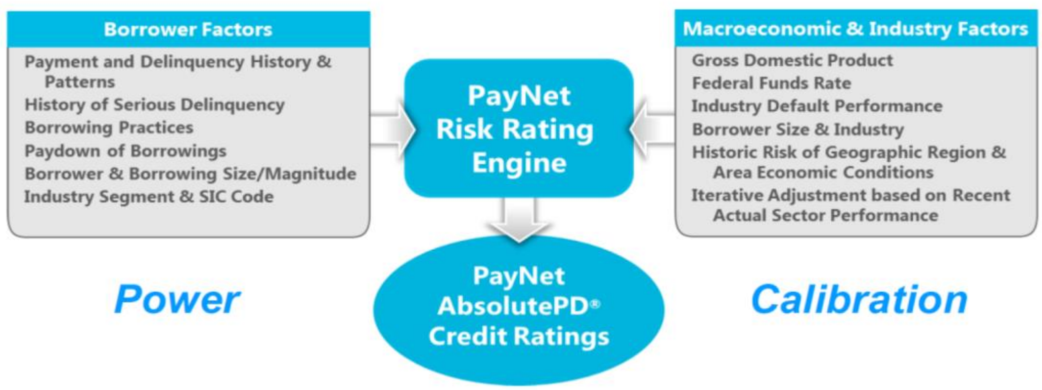


Figure 4: Technology Adoption in the SME Lending Market—PayNet

This figure provides excerpts from an advertisement by the U.S. equipment finance credit bureau, PayNet (emphasis added).



Financial statements not required

PayNet reduces your lending risk by providing an absolute measure of credit risk at both the borrower and portfolio level on millions of small businesses for which financial statements are not available. PayNet's AbsolutePD product provides the only probability of defaults for private companies by geographic regions, industry sectors, and loan exposures.

PayNet AbsolutePD provides a consistent, transparent and objective loan management process mandated by management, auditors, regulators CEO's and investors.

PayNet AbsolutePD:

- Rates millions of private companies for which current and/or reliable financial statements are not available

Figure 5: Technology Adoption in the SME Lending Market

This figure provides website excerpts from several vendors (Rutter, Enigma, and Tax Status) specializing in providing alternative information and other tools to commercial lenders.

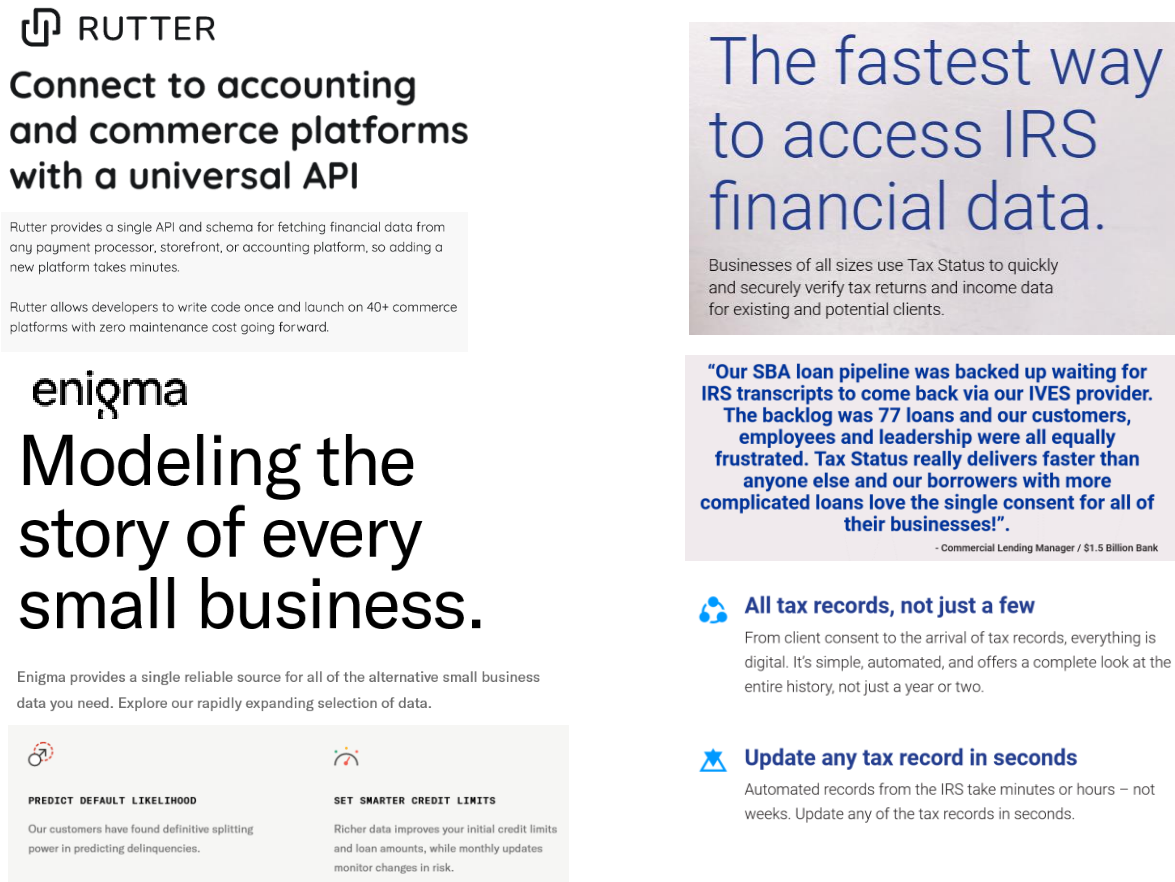
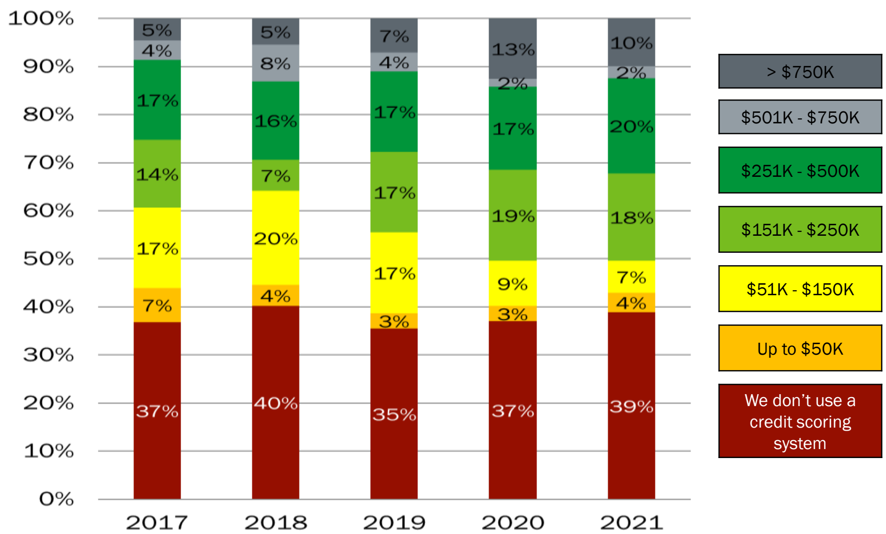


Figure 6: Credit Managers Survey

This figure presents responses to the 10th annual Credit Managers Survey, conducted by the Equipment Lease and Finance Association (ELFA 2021). The "Credit Scoring Threshold" refers to the loan size credit managers report being authorized to approve based on credit scores alone. Panel B reports credit application turnaround times by lender type.

Panel A: Credit Scoring Threshold



Panel B: Credit Application Turnaround Times for Loans within Credit Scoring Threshold

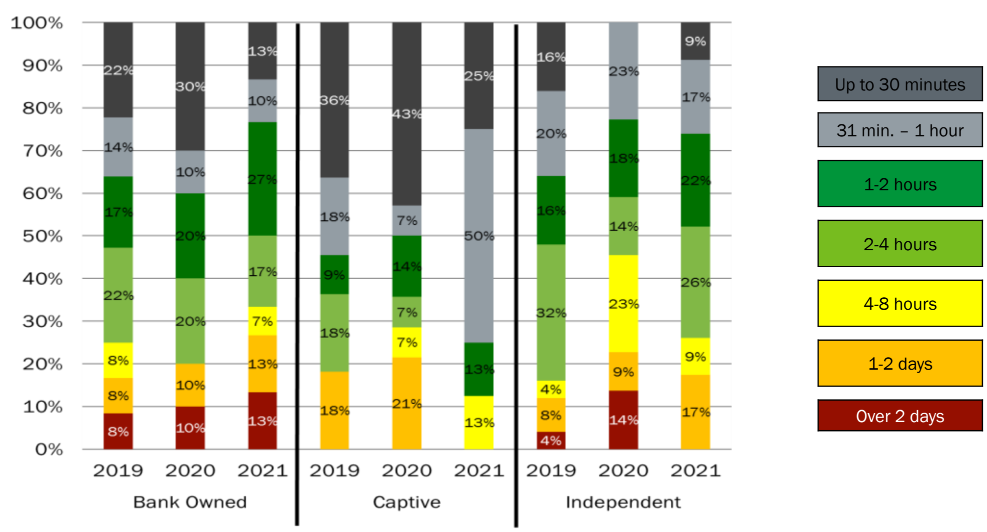


Figure 7: Originations by Lender Type

This figure presents the number of UCC filings (in thousands) in the EDA dataset for banks and nonbanks since 1997.

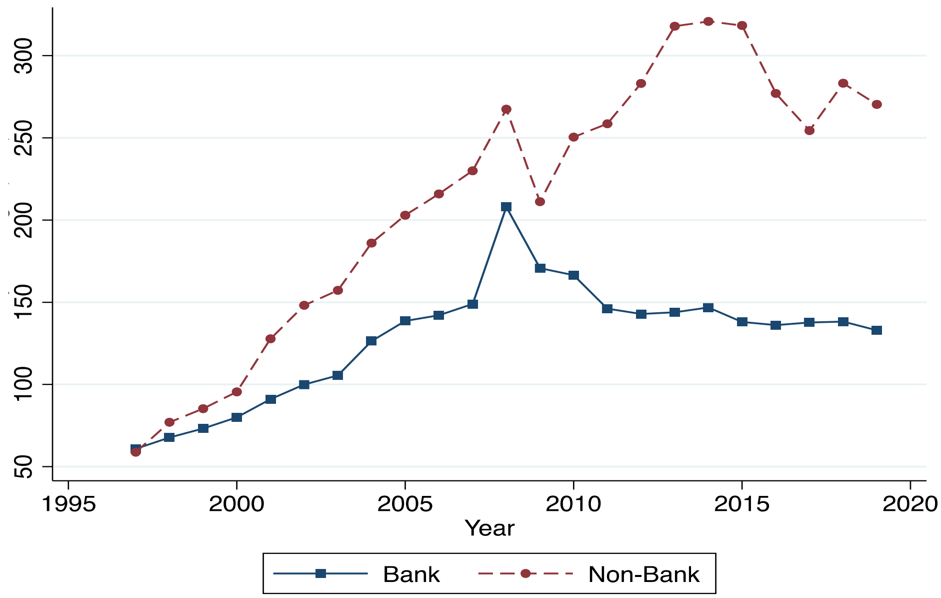
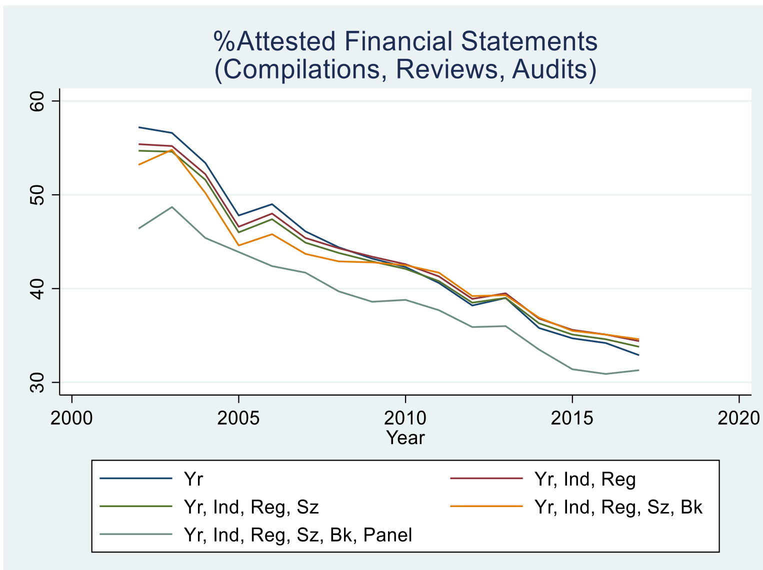


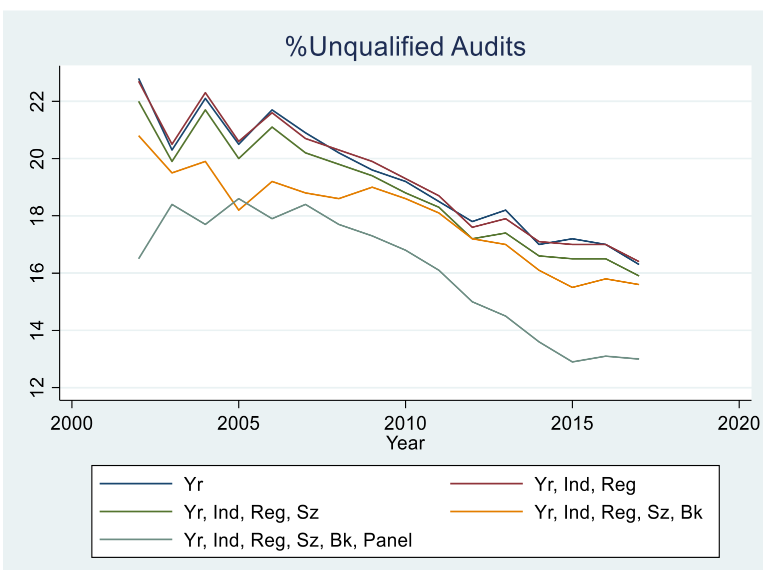
Figure 8: Banks' Financial Statement Collection

This figure plots banks' financial statement collection rates between 2002 and 2017. Panel A (B, C, D) models the percent of statements collected that are Attested Financial Statements (Unqualified Audits, Reviews, Compilations). Each panel plots the year fixed effects from a regression with different fixed effects, controls, and samples as labeled in the legend. *Yr*, *Ind*, *Reg*, and *Bk* refer to year, three-digit industry, region, and bank fixed effects, respectively. *Sz* refers to a control for log average borrower sales. *Panel* refers to a constant panel of banks participating in RMA every year between 2002 and 2017. The unit of observation in the regression is bank-industry-region-year.

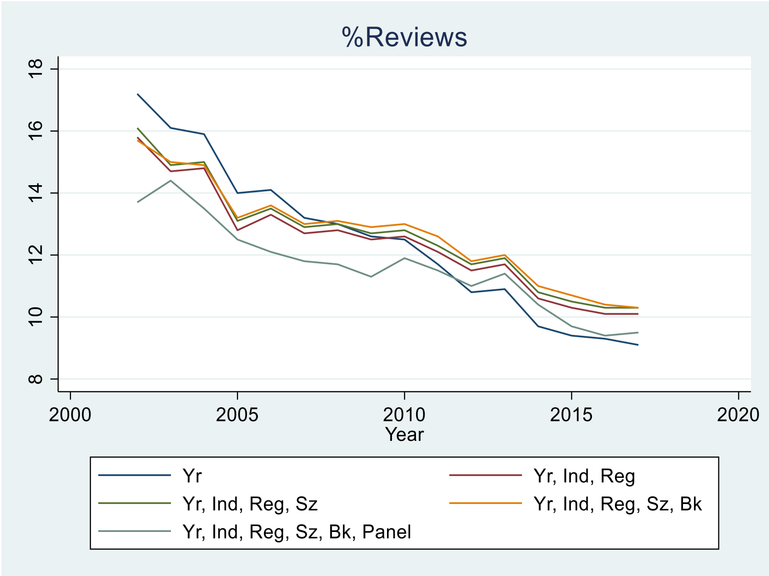
Panel A: Attested Financial Statements



Panel B: Unqualified Audits



Panel C: Reviews



Panel D: Compilations

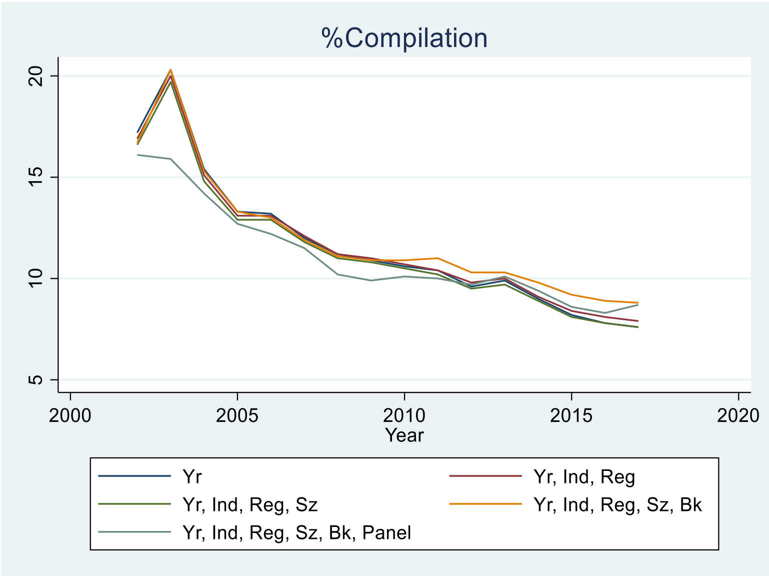
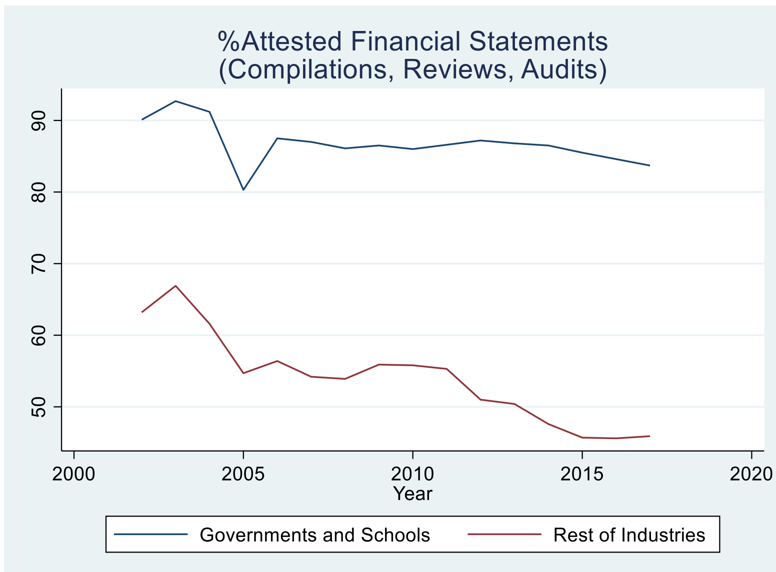


Figure 9: Banks' Financial Statement Collection

This figure plots banks' financial statement collection rates between 2002 and 2017 for two subsamples: (1) governments and schools, and (2) all other industries. Panel A (B) models the percent of statements collected that are Attested Financial Statements (Unqualified Audits). Each panel plots the year fixed effects from a regression with year, industry, region, and bank fixed effects and a control for log average borrower sales. The sample is limited to borrowers with $25 million or more of revenue. The unit of observation in the regression is bank-industry-region-year.

Panel A: Attested Financial Statements



Panel B: Unqualified Audits

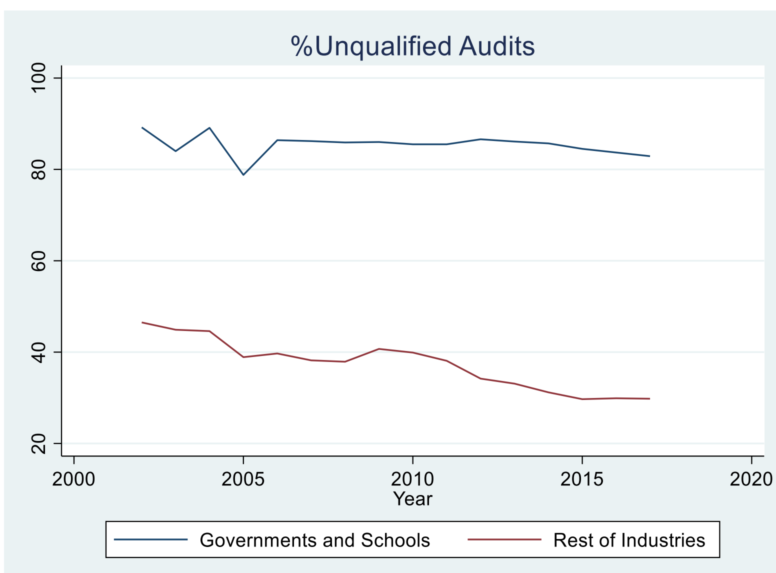


Figure 10: CPA Deserts and Lending

This figure plots the coefficients from a piecewise version of equation (2) using event year indicators. At t=0, the county becomes a CPA desert, defined as having zero CPA firms. The dependent variable is *Log Filings*, one plus the log number of UCC filings that county-year for banks or nonbanks. The lines plot 95% level confidence intervals. The holdout period is t=-2.

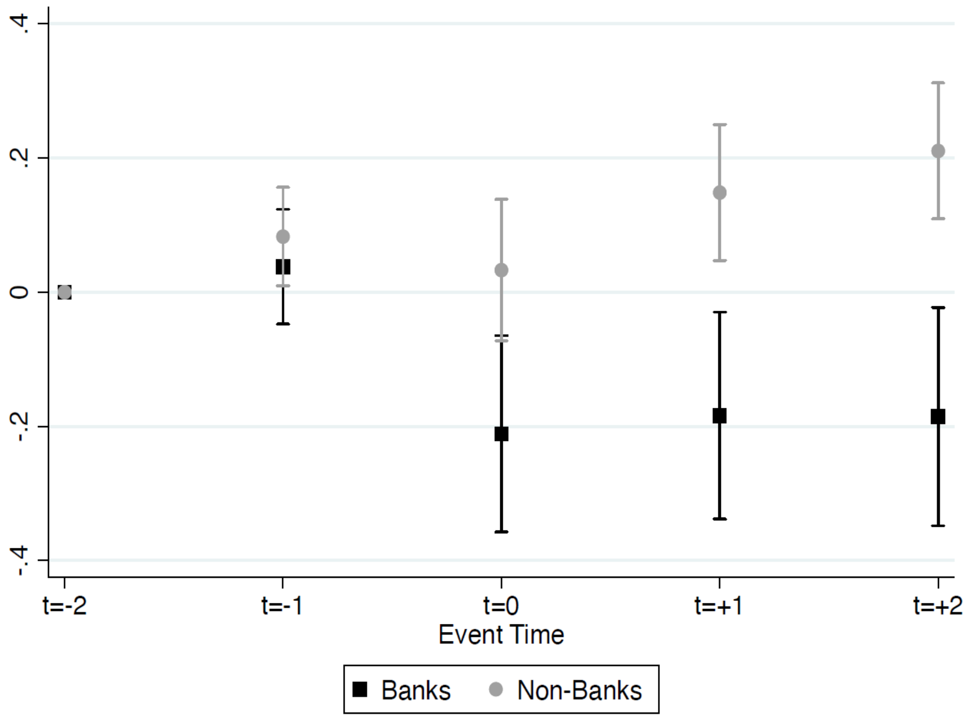


Figure 11: Variable Definitions

	Definition
AFS	The proportion of financial statements collected by banks that are unqualified audits, reviews, or compilations (i.e., attested financial statements).
Unqualified	The proportion of financial statements collected by banks that are unqualified audits.
Reviews	The proportion of financial statements collected by banks that are reviews.
Compilations	The proportion of financial statements collected by banks that are compilations.
Avg Borrower Size	The ratio of total firm sales for all of the bank's exposures to the number of statements.
Tech Adoption Rate	The proportion of contracts originated in that industry-state-year by lender members of the PayNet credit bureau.
Placebo Tech Adoption Rate	The *Tech Adoption Rate* from a randomly chosen other industry in the same state.
Filings	The number of UCC filings.
Value	The dollar value of equipment securing the UCC filing.
Bank	An indicator variable equal to one for bank lenders, and zero otherwise.
Nonbank	An indicator variable equal to one for nonbank lenders, and zero otherwise.
CPA Firms	The number of CPA firms licensed in a county-year.
CPA Firms (Census)	The number of CPA firms operating in a county-year, based on census data. We identify CPA firms based on having NAICS code 541211.
CPA Desert	An indicator variable equal to one for county-years with no licensed CPA firms, and zero otherwise.
Post High Nonbank Growth	An indicator variable equal to one for county-years where the nonbank growth in filings over each of the previous two years exceeds the threshold labeled in the table (e.g., 10%).
C&I Chargeoffs	The ratio of C&I loan chargeoffs to lagged C&I loans.
ROA	The ratio of net income to lagged assets.

Table 1: Sample Composition—RMA Dataset

This table describes the composition of our RMA sample.

# Financial Reports	2,909,131
# Bank-Industry-Region-Year observations	258,119
# Bank-Years	4,519
# Banks	821

Table 2: Summary Statistics

This table provides summary statistics for variables in our analyses, as labeled. See Figure 12 for variables definitions.

Panel A: Figures 1, 8, 9

	Mean	Std Dev	25%	50%	75%	N
AFS	0.47	0.39	0.00	0.50	0.92	258,119
Unqualified	0.22	0.34	0.00	0.00	0.33	258,119
Reviews	0.12	0.24	0.00	0.00	0.13	258,119
Compilation	0.13	0.26	0.00	0.00	0.14	258,119
Number of Statements	11	47	1	2	7	258,119

Panel B: Tables 3-6

	Mean	Std Dev	25%	50%	75%	N
Filings (Banks)	32.08	65.49	6.00	15.00	34.00	43,470
Filings (Nonbanks)	73.05	121.63	16.00	40.00	86.00	43,470
Value (Banks)	3,790,000	12,100,000	353,000	1,130,000	3,030,000	43,470
Value (Nonbanks)	6,680,000	15,000,000	989,000	2,760,000	6,900,000	43,470
CPA Firms	20.10	77.31	0.00	2.00	9.00	43,470
CPA Desert	0.29	0.45	0.00	0.00	1.00	43,470
Tech Adoption Rate	0.82	0.30	0.75	1.00	1.00	10,211

Table 3: Technology Adoption and AFS Collection by Banks

This table models AFS collection by banks using Equation (1). The unit of observation is industry-state-year. The dependent variable in Panel A (B) is *Unqualified (AFS)*, the proportion of financial statements collected by banks in that industry-state-year that are unqualified audits (unqualified audits, reviews, or compilations). *Tech Adoption Rate* is the proportion of contracts originated in that industry-state-year by lender members of the PayNet credit bureau. *Placebo Tech Adoption Rate* is the *Tech Adoption Rate* from a randomly chosen industry in the same state and year. *Log Avg Borrower Size* is the log of the average borrower sales in the industry-state-year. Industry is based on three-digit NAICS. Lender Type x Year FEs refer to a series of indicators for average lender characteristics in the industry-state-year (size tercile, collateral specialization, and industry specialization) interacted with year indicators. See Figure 11 for variables definitions. Reported below the coefficients are standard errors double clustered at the state and industry level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: AFS

	(1) AFS	(2) AFS	(3) AFS	(4) AFS
Tech Adoption Rate$_t$	-0.017*	-0.021**	-0.026**	
	[0.009]	[0.008]	[0.012]	
Log Avg Borrower Size	0.011***	0.011***	0.011***	0.013***
	[0.003]	[0.002]	[0.003]	[0.002]
Tech Adoption Rate$_{t-1}$			0.017	
			[0.011]	
Tech Adoption Rate$_{t-2}$			0.016	
			[0.016]	
Placebo Tech Adoption Rate$_t$				0.007
				[0.012]
Adj R-Sq.	0.480	0.483	0.521	0.474
N	10,089	10,087	6,012	7,809
Industry x Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Lender Type x Year FE	No	Yes	No	No

Panel B: Unqualified Audits

	(1) Unqualified	(2) Unqualified	(3) Unqualified	(4) Unqualified
Tech Adoption Rate$_t$	-0.012**	-0.011**	-0.013**	
	[0.005]	[0.004]	[0.006]	
Log Avg Borrower Size	0.010***	0.010***	0.010***	0.010***
	[0.002]	[0.002]	[0.002]	[0.002]
Tech Adoption Rate$_{t-1}$			-0.007	
			[0.009]	
Tech Adoption Rate$_{t-2}$			0.002	
			[0.006]	
Placebo Tech Adoption Rate$_t$				0.006
				[0.007]
Adj R-Sq.	0.627	0.628	0.660	0.623
N	10,089	10,087	6,012	7,809
Industry x Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Lender Type x Year FE	No	Yes	No	No

Table 4: CPA Firms and Credit by Lender Type

This table models credit originations using Equation (2). The unit of observation is county-lender type-year. The dependent variable in columns 1 and 2 (3 and 4) is *Log Filings (Log Value)*, one plus the log number of UCC filings (log dollar value of equipment financed) that county-year for banks or nonbanks (the two lender types). *Log CPA Firms* is one plus the log number of CPA firms in the county-year. See Figure 11 for variables definitions. Reported below the coefficients are standard errors clustered at the county level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Log Filings		Log Value	
Log CPA Firms x Bank	0.348***	0.169***	2.004***	1.862***
	(0.021)	(0.019)	(0.120)	(0.110)
Log CPA Firms x Nonbank	0.197***		0.646***	
	(0.018)		(0.083)	
P-value for coefficient difference	0.000		0.000	
County x Lender Type FE	Yes	Yes	Yes	Yes
Lender Type x Year FE	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes
N	86,940	86,940	86,940	86,940
Adjusted R2	0.873	0.900	0.624	0.687

Table 5: Robustness

This table models credit originations using modified versions of Equation (2). The unit of observation is county-lender type-year. The dependent variable is *Log Filings*, one plus the log number of UCC filings that county-year for banks or nonbanks. In column 1, we use census data to measure the number of CPA firms. In column 2, *CPA Desert* is an indicator variable for county-years with zero CPA firms. In column 3, we introduce state x lender type x year fixed effects. See Figure 11 for variables definitions. Reported below the coefficients are standard errors clustered at the county level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1) Log Filings	(2) Log Filings	(3) Log Filings
Log CPA Firms (Census) x Bank	0.249***		
	(0.016)		
CPA Desert x Bank		-0.149***	
		(0.027)	
Log CPA Firms x Bank			0.253***
			(0.018)
County x Lender Type FE	Yes	Yes	Yes
Lender Type x Year FE	Yes	Yes	No
County x Year FE	Yes	Yes	Yes
State x Lender Type x Year	No	No	Yes
N	86,940	86,940	86,940
Adjusted R2	0.902	0.900	0.917

Table 6: Time Series Evidence

This table models credit originations using Equation (2). The unit of observation is county-lender type-year. The dependent variable in Panel A (B) is *Log Filings (Log Value)*, one plus the log number of UCC filings (log dollar value of equipment financed) that county-year for banks or nonbanks. *Log CPA Firms* is one plus the log number of CPA firms in the county-year. The sample in each column is limited to the years labeled. See Figure 11 for variables definitions. Reported below the coefficients are standard errors clustered at the county level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Filings

	(1)	(2)	(3)	(4)
	Log Filings			
Log CPA Firms x Bank	0.709***	0.400***	0.415***	0.194***
	(0.040)	(0.047)	(0.042)	(0.032)
Log CPA Firms x Nonbank	0.433***	0.253***	0.107**	0.008
	(0.053)	(0.068)	(0.042)	(0.013)
Period	2000-2004	2005-2009	2010-2014	2015-2019
County x Lender Type FE	Yes	Yes	Yes	Yes
Lender Type x Year FE	Yes	Yes	Yes	Yes
N	18,910	18,910	18,910	18,910
Adjusted R2	0.867	0.928	0.947	0.954

Panel B: Value

	(1)	(2)	(3)	(4)
	Log Value			
Log CPA Firms x Bank	4.476***	3.294***	3.921***	1.698***
	(0.212)	(0.333)	(0.320)	(0.234)
Log CPA Firms x Nonbank	2.362***	1.512***	0.714***	0.106
	(0.276)	(0.366)	(0.268)	(0.067)
Period	2000-2004	2005-2009	2010-2014	2015-2019
County x Lender Type FE	Yes	Yes	Yes	Yes
Lender Type x Year FE	Yes	Yes	Yes	Yes
N	18,910	18,910	18,910	18,910
Adjusted R2	0.663	0.734	0.736	0.736

Table 7: Nonbank Growth and Sensitivity of Bank Lending to CPA Supply

This table models credit originations as a function of CPA supply and nonbank growth. The unit of observation is county-year. The dependent variable is Δ *Filings*, the year-to-year change in banks' UCC filings in a given county. Δ *CPA Firms* is the year-to-year change in the number of CPA firms in a given county. *Post High Nonbank Growth* is an indicator equal to one when in each of the previous two years, the county experienced nonbank lending growth larger than the threshold labeled at the bottom of the table. See Figure 11 for variables definitions. Reported below the coefficients are standard errors clustered at the county level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Filings	Δ Filings	Δ Filings	Δ Filings	Δ Filings	Δ Filings
Post High Nonbank Growth x Δ CPA Firms	-0.366	-0.418**	-0.415	-0.797***	-1.071**	-0.852**
	(0.255)	(0.211)	(0.314)	(0.305)	(0.455)	(0.425)
Δ CPA Firms	0.356***	0.362***	0.298***	0.326***	0.293***	0.220*
	(0.118)	(0.131)	(0.104)	(0.118)	(0.108)	(0.128)
Post High Nonbank Growth	-1.993***	-1.809***	-1.600***	-1.506***	-1.291***	-1.849***
	(0.206)	(0.232)	(0.288)	(0.307)	(0.348)	(0.334)
High Nonbank Growth Threshold	10%	15%	20%	25%	30%	35%
N	30,118	30,118	30,118	30,118	30,118	30,118
Adjusted R2	0.004	0.004	0.004	0.006	0.006	0.003

Table 8: Bank-level Consequences of AFS Decline

This table models bank C&I chargeoffs and ROA as a function of AFS collection, fixed effects, and bank controls. The unit of observation is bank-year. The dependent variable in Panel A (B) is C*&I Chargeoffs*, one hundred times the ratio of chargeoffs to total loans (ROA). *AFS (Unqualified)*, is the proportion of financial statements collected by banks that in state-year that are unqualified audits, reviews, or compilations (unqualified audits). *Residential*, *Commercial Real Estate*, *Household*, *C&I*, and *Agricultural* refer to loans outstanding of each type scaled by total assets. *Trading Assets*, *Deposits*, and *Equity* are scaled by total assets. See Figure 11 for variables definitions. Reported below the coefficients are standard errors clustered at the bank level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: C&I Chargeoffs

	(1) C&I Chargeoffs	(2) C&I Chargeoffs	(3) C&I Chargeoffs	(4) C&I Chargeoffs	(5) C&I Chargeoffs	(6) C&I Chargeoffs
AFS_{t-1}	0.640	0.182	0.663			
	(0.452)	(0.421)	(0.455)			
$Unqualified_{t-1}$				0.698	0.295	0.479
				(0.934)	(0.851)	(0.911)
Log $Assets_{t-1}$	0.957**	0.324	0.574	0.965**	0.324	0.583
	(0.442)	(0.468)	(0.422)	(0.442)	(0.467)	(0.422)
Loan $Growth_{t-1}$	-0.129**	-0.088	-0.094**	-0.131**	-0.089	-0.096**
	(0.054)	(0.054)	(0.045)	(0.054)	(0.054)	(0.045)
$Residential_{t-1}$	0.552	-0.317	-0.936	0.599	-0.287	-0.899
	(1.377)	(1.106)	(1.279)	(1.380)	(1.124)	(1.287)
Commercial Real $Estate_{t-1}$	-0.128	-2.230**	-3.160***	-0.113	-2.220**	-3.134***
	(1.015)	(1.012)	(1.106)	(1.021)	(1.011)	(1.105)
$Household_{t-1}$	-1.377	-2.013	-2.047	-1.410	-2.009	-2.028
	(1.802)	(1.459)	(1.767)	(1.804)	(1.463)	(1.767)
$C\&I_{t-1}$	-1.708	-1.523	-2.275*	-1.724	-1.529	-2.298*
	(1.326)	(1.114)	(1.377)	(1.331)	(1.117)	(1.386)
$Agricultural_{t-1}$	4.065	5.587	0.637	4.131	5.641	0.657
	(5.029)	(5.574)	(4.319)	(5.022)	(5.559)	(4.315)
Trading $Assets_{t-1}$	25.633**	-16.189	-10.546	24.952**	-16.485	-11.214
	(10.034)	(10.442)	(9.794)	(10.034)	(10.448)	(9.633)
$Deposits_{t-1}$	-0.037	0.677	0.926	-0.016	0.665	0.890
	(1.643)	(1.437)	(1.601)	(1.641)	(1.441)	(1.604)
$Equity_{t-1}$	-3.472	-8.941	-8.048	-3.365	-8.889	-7.802
	(5.594)	(6.137)	(5.324)	(5.621)	(6.149)	(5.334)
N	2,171	1,526	2,171	2,171	1,526	2,171
Adjusted R2	0.295	0.320	0.324	0.295	0.320	0.323
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Drop 2007-2010	No	Yes	No	No	Yes	No
Controls x 2007-2010	No	No	Yes	No	No	Yes

Panel B: ROA

	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) ROA	(6) ROA
AFS_{t-1}	0.039	-0.004	0.012			
	(0.062)	(0.053)	(0.056)			
$Unqualified_{t-1}$				0.117	0.118	0.120
				(0.122)	(0.086)	(0.108)
Log $Assets_{t-1}$	0.011	0.129	0.012	0.010	0.129	0.011
	(0.102)	(0.103)	(0.094)	(0.102)	(0.103)	(0.094)
Loan $Growth_{t-1}$	0.047	0.068	0.065*	0.047	0.068	0.064*
	(0.037)	(0.046)	(0.037)	(0.037)	(0.046)	(0.037)
$Residential_{t-1}$	0.331	0.366*	0.490**	0.338	0.380*	0.501**
	(0.242)	(0.205)	(0.227)	(0.241)	(0.203)	(0.227)
Commercial Real $Estate_{t-1}$	-0.017	0.363***	0.338**	-0.016	0.366***	0.340**
	(0.137)	(0.133)	(0.140)	(0.137)	(0.133)	(0.140)
$Household_{t-1}$	-0.162	-0.059	0.007	-0.160	-0.056	0.013
	(0.171)	(0.172)	(0.187)	(0.172)	(0.172)	(0.188)
$C\&I_{t-1}$	0.231	0.142	0.249	0.230	0.144	0.250
	(0.204)	(0.167)	(0.202)	(0.203)	(0.165)	(0.201)
$Agricultural_{t-1}$	0.203	0.619	0.482	0.222	0.643	0.507
	(0.753)	(0.813)	(0.855)	(0.747)	(0.811)	(0.851)
Trading $Assets_{t-1}$	-3.305	-0.322	-1.783	-3.385	-0.418	-1.888
	(2.064)	(1.872)	(1.632)	(2.053)	(1.902)	(1.637)
$Deposits_{t-1}$	0.733***	0.464**	0.529**	0.733***	0.461**	0.527**
	(0.213)	(0.187)	(0.207)	(0.212)	(0.186)	(0.206)
$Equity_{t-1}$	-1.398*	-0.113	-0.394	-1.391*	-0.119	-0.396
	(0.813)	(0.952)	(0.926)	(0.812)	(0.946)	(0.923)
N	2,207	1,568	2,207	2,207	1,568	2,207
Adjusted R2	0.598	0.728	0.617	0.598	0.728	0.617
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Drop 2007-2010	No	Yes	No	No	Yes	No
Controls x 2007-2010	No	No	Yes	No	No	Yes

Appendix A: Risk Management Association Data Description[1]

Overview

The Risk Management Association (RMA) is a not-for-profit professional association serving the financial services industry. Its mission is "to advance enterprise-wide risk management in the financial services industry through education, products, and community." Its membership consists of "1,600+ financial institutions of all sizes, from multi-nationals to local community banks [and] these institutions are represented by over 41,000 individual RMA members located throughout North America, Europe, Australia, and Asia."

RMA has been publishing the RMA Statement Studies® for over a century and describes it as "a staple credit risk tool for more than 100 years, with historical and comparative financial data of US-based businesses since 1919." The purpose of these studies is to provide financial institutions (hereafter, banks) with benchmarking data to better understand the financial performance of commercial borrowers and prospects. Data for these studies are collected annually. Each year, RMA begins its campaign to encourage members to participate. Participating banks typically have a deadline of June or July of each year to provide annual financial statements that they have collected from a borrower or prospect from April 1 of the previous year to March 31 of the current year. Historically banks have submitted their financial statements manually (e.g., via mail and fax); however, the predominant form of submission more recently is electronic submission (for example, in 2014, 95% of the financial statements submitted by banks were provided electronically). Several software packages that banks use to analyze commercial loans have a compatible export feature, allowing banks to simply push the "submit" button to create an RMA submission file.

RMA member banks collect financial statements from commercial borrowers in all industries, sizes, and loan grades or risk ratings. However, as quoted from the RMA Handbook, observations will be rejected if any one of the following is not true:

- The fiscal year must fall within the current period—only 12-month fiscal statements falling between 4/1 to 3/31 are acceptable.
- The balance sheet must balance.
- The legal form of the entity must be noted.
- The type of financial statement must be noted.
- A valid NAICS or SIC code must be present. RMA accepts either an SIC code (four-digit) or a NAICS code (six-digit). RMA strongly encourages submission via 2012 NAICS.
- The income statement must be complete.

Importantly, statements are rejected if a valid industry and statement type are not included. This mitigates concerns that industries or statement types classified as "other" are simply picking up "missing" observations. RMA indicates that their credo is "contribute every statement you have," so they make a concerted effort to have each bank submit their entire portfolio of statements. For the publicly available Annual Statement Studies, RMA truncates firms with assets above $250 million. For purposes of our study, however, RMA did not eliminate observations with more than $250 million in assets to provide the best proxy for a bank's portfolio.

[1] This section quotes frequently from RMA's homepage (www.rmahq.org) as accessed on March 17, 2023.

The dataset that RMA provided to us is aggregated at the bank-industry-region-borrower size category-year level. The regions include the Northeast, Southeast, Central, South Central, North Central, and West. The size categories include <$1 million, $1-$3 million, $3-5 million, $5-$10 million, $10-$25 million, or >$25 million of revenue.

For each unit of observation, RMA tabulated for us the number of financial statements into one of five mutually exclusive, collectively exhaustive categories—unqualified audit, review, compilation, tax return, and other (see below for additional detail about these statement types)—and the total sales ($) for all borrowers within the unit of observation.

Several important points and caveats regarding this dataset are worth noting:

- The data are not collected from a random sample of banks. Banks volunteer to participate. To the extent that this creates omitted variable selection bias in the data, we cannot control for this bias; however, the results reported in the paper are robust to including only those banks that participate in each year. Moreover, banks that choose to participate in RMA tend to be larger than banks that do not participate—i.e., these are the more important banks for our study from a generalizability perspective. In most years, at least eight of the 10 largest U.S. banks participate.
- There is no guarantee that the data represent the entire bank portfolios. RMA only "encourages" banks to submit all financial statements. Moreover, banks do not collect any financial statements for a minority of their smallest borrowers (Minnis and Sutherland 2017). However, given the simple electronic submission process and the high correlation between the number of statements individual banks submit to RMA and their commercial lending portfolios as tabulated in Call Reports (Berger, Minnis, and Sutherland 2017), we believe that the RMA dataset is a very reasonable proxy for the banks' commercial lending portfolios.
- See Tables A1-A4 of the online appendix to Berger, Minnis, and Sutherland (2017) for additional analyses investigating the banks participating in the RMA dataset.

Statement Types

As noted above, RMA tabulates the number of financial statements collected by members into one of five different types: unqualified audit, review, compilation, tax returns, and other. In this section, we describe the process RMA uses to identify the statement types and then describe each of the five statement types.

Process

RMA receives "raw" descriptions of the financial statements that members submit to RMA and then RMA, in turn, maps those raw descriptions into the five financial statement categories. RMA provided to us the complete list of raw financial statement type descriptions reported by members for the 2012, 2017, and 2022 submission cycles. In those years, there were roughly 80 different statement types. The vast majority of these descriptions have obvious mappings into one of the five statement categories and are simply slight iterations from the primary description. For example, in 2022 there are five descriptions for "Compilation": Compiled, C, COMP, CPA Compiled, and Compilation. Unqualified Audits, Reviews, and Tax Returns categories have similar descriptions and have 5, 5, and 8 different line items, respectively. The remaining 60 descriptions are classified as "Other" by RMA. We describe the statement types in more detail below.

Unqualified Audit

A financial statement audit provides positive assurance that the financial statements are reported in accordance with Generally Accepted Accounting Principles. An unqualified audit opinion indicates that the auditor believes that the financial statements are materially in accordance with GAAP. Unqualified audited financial statements are accompanied by complete footnote disclosure, providing the most complete set of information of all of the statement along with the highest level of assurance and no detected material deviations from GAAP.

Review

Financial statement reviews provide negative assurance. An independent accountant performs analytical procedures (e.g., ratio analyses) and interviews management to assess whether the financial statements are misstated; however, the accountant does not perform substantive procedures to obtain positive evidence of an account balance. Reviews are generally accompanied by complete footnote disclosure; therefore, reviewed financial statements provide a similar information set to unqualified audits, but the information has a significantly lower level of assurance, reporting quality, and cost.

Compilation

A compilation provides no assurance about the financial statement balances reported in the financial statements. An accountant puts the firm's financial information in the form of financial statements but performs no procedures and provides no assurance as to the reporting quality. Compilations include all three standard financial statements, but are not required to report (and generally omit) footnote disclosures. Therefore, compilations provide substantially less assurance and information than either audits or reviews.

Tax Return

All firms are required to file a tax return with the Internal Revenue Service (IRS) annually. The nature of these returns differs by entity type (e.g., C Corporation, S Corporation, or Limited Liability Company) and entity size (e.g., firms with less than $250,000 in assets are not required to complete Schedule L which is a balance sheet). While all firms follow "tax basis" accounting to complete the form, the tax basis may differ based on firm size and various options that firms are able to elect (e.g., accrual versus cash basis; differing depreciation options, etc.). Therefore, even within the tax basis of accounting, the differing forms and various options result in heterogeneity. The focus of tax returns is the income statement, but firms with more than $250,000 of assets also must provide a balance sheet. Important omissions from tax returns include both the statement of cash flows and financial footnotes. Moreover, while independent accountants are frequently involved in the production of these statements, they generally do not provide assurance about them. However, the IRS serves an implicit monitoring role, though the vast majority returns are not audited on an annual basis by the IRS. Collectively, tax returns provide useful but limited financial information and have some, but weaker (and implicit) verification.

Other

The "Other" category captures all statements that are not one of the above. Based on our analysis of the detailed statement type descriptions provided to us by RMA, the overwhelming majority of "Other" are company prepared financial statements. Various iterations of "Company Prepared" represent nearly 80% of the financial statements in this category. Company prepared financial statements are those prepared internally by management and provided to the bank without the involvement of an external accountant. The fact that company prepared comprises the bulk of this category is consistent with discussions with RMA. Moreover, they have indicated that this description has appeared more frequently over time. The remaining set of financial statement types can be essentially grouped into one of three categories: (i) some form of phrasing such as “other” or “unaudited” (representing just over 5% of the “Other” category in 2022); (ii) some form of “qualified audit” (representing just under 5% of the “Other” category); (iii) a variety of other descriptions, such as “TTM” or “Trailing 12 Mo.” or “ROLL STMT”.[2]

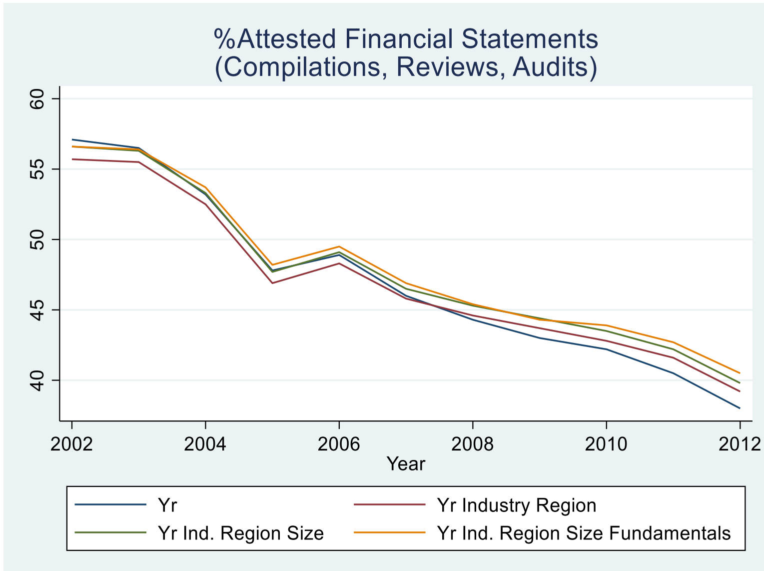
The vast majority of the financial statements classified as “Other” suggest this category identifies the variation we are attempting to measure: financial statements not prepared by independent CPA firms, and, specifically instead, prepared by management. The one exception are those statements identified in some manner as “Qualified audits.” Qualified audit reports are audits similar to “unqualified” audit reports described above but a qualification was made regarding some aspect of the financial statements. For example, the company prefers not to follow a particular accounting rule, so the independent accounting firm provides an “except for” opinion which states that the financial statements follow GAAP except for this aspect. Historically, RMA reported qualified statements as a separate category, but because this category was infrequently used, RMA began consolidating it with “other” (including for the full time period of the data we use in our paper). Our analyses of the 2012, 2017, and 2022 raw financial statement type descriptions indicate qualified statements comprise a constant share (roughly 5%) of “other” statements, thus playing no meaningful role in explaining the AFS decline. In sum, company prepared financial statements make up a large majority of financial statements in the “Other” category.

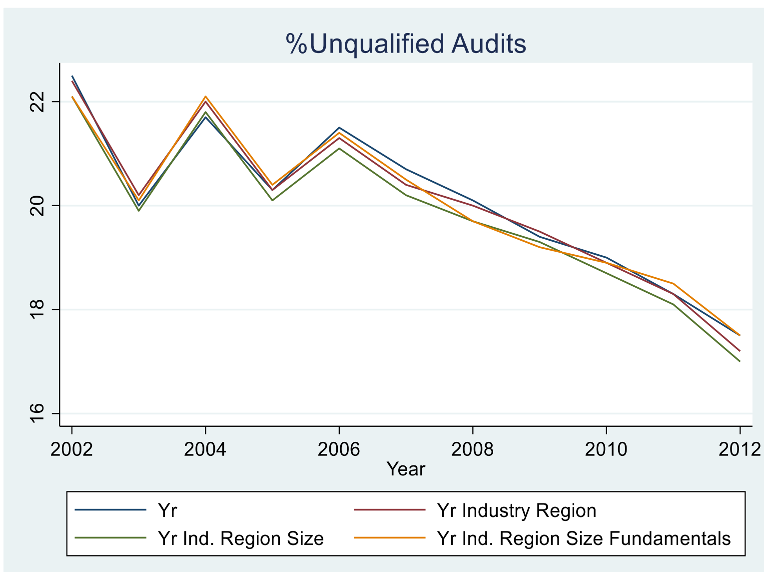
[2] We also note that a very small number of financial statements in the “Other” category have the description of “10-K” or “10-Q”. Given that at least the 10-K financial statements would be audited, this could be concerning, but the entirety of the financial statements collected with this description represent less than 0.1% of financial statements classified as “Other.”

Appendix B: Supplemental Analyses

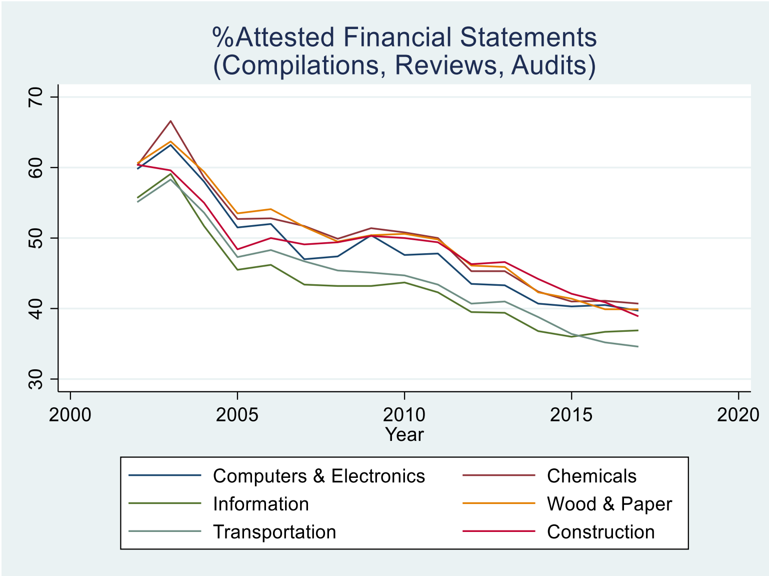
This section contains supplemental plots of AFS collection. Each panel adds controls or splits the sample as labeled.

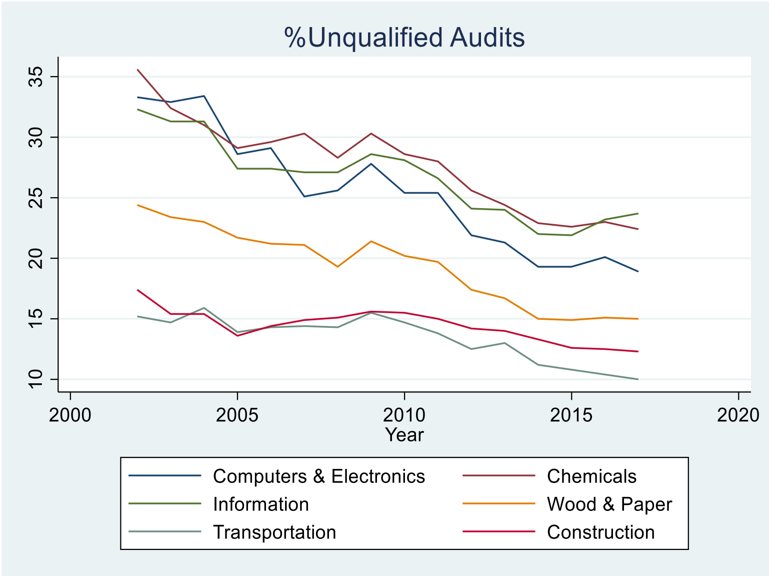
Panel A: Controling for Borrower Fundamentals



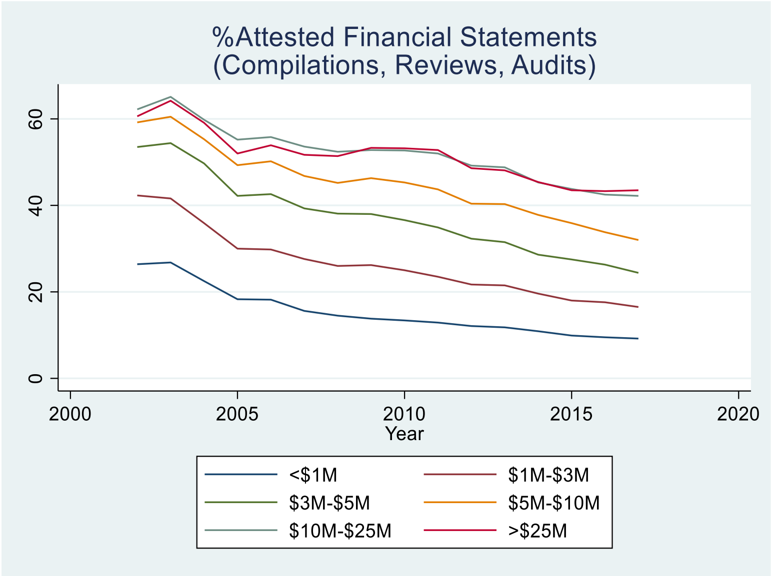


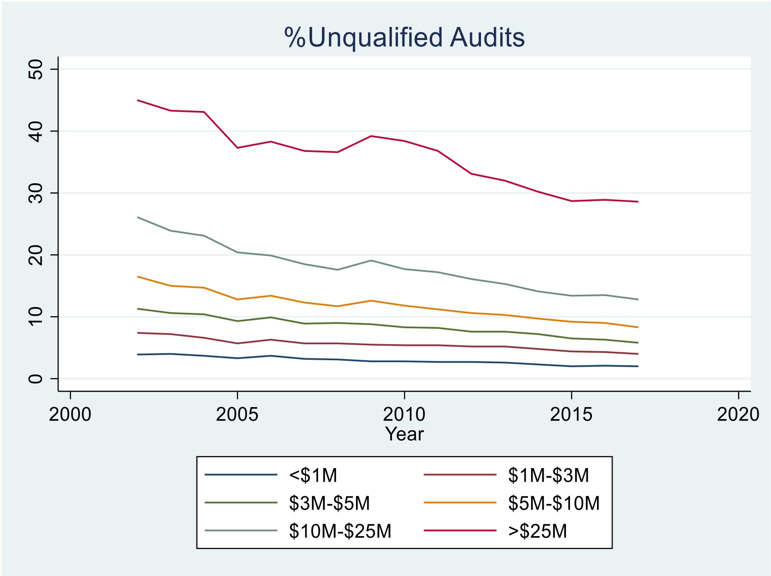
Panel B: Trend by Sector





Panel C: Trend by Borrower Size Group





Panel D: Trend by Bank Size