US Community Bank Failure: An Empirical Investigation

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There are clear differences in institutional risk profiles between community and non-community banks. We hypothesize that these dissimilarities impact community bank failure risk through bank-specific covariates relating to asset quality and earnings in a way that is disparate from the salient findings in the literature on non-community banks. Consistent with our differential impact hypothesis we find that community banks which reduce their proportion of consumer lending or compensation, as a percentage of total assets, have increased failure risk. These findings appear to be unique to the community banking industry.

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1. Introduction

The community banking industry has long been a pivotal cornerstone in US financial sector intermediation. The importance of this characteristically American enterprise stems from its unique relationship lending services based on the knowledge and history of their generally smaller, rural clientele. The inherent flexibility and willingness of community banks to work with their customers comes in stark contrast to big bank processes which are best described as transactional, quantitative, and standardized. However, the last 40 years have seen the overall number of small, locally owned community lenders markedly shrink. The savings and loan crisis of the 1980's saw the first culling of the industry. This was followed by broad sweeping changes in regulation and industry practices in the early 1990's that effectively removed the barriers to bank consolidation. Finally, the far-reaching financial shocks of the 2007 global financial crisis propelled the most recent attenuation of community banks.[1] The 2012 Federal Deposit Insurance Corporation (FDIC) community banking study reported that the share of US credit market debt held by small financial intermediaries declined by almost 50 percent between 1984 and 2011, and the share of banking assets held by community banks declined from 38 percent to 14 percent over the same period. Lux and Greene (2015) show a similar weakening of the community bank lending-market over the last two decades, but report a much larger

[1] Hassan and Hippler (2014) report a decline of approximately 50 percent in the number of institutions from 1993 to 2013.

decline, of roughly 50 percent, in total banking assets.

Despite these changes to the banking industry, community banks continue to play a critical role in key lending segments of the US economy. Lux and Greene (2015) report that community banks provide approximately 77 percent of agricultural loans and 50 percent of small business loans. Furthermore, community banks play a pivotal role in real estate lending, particularly for housing, where knowledge of local market conditions and borrowers is paramount.[2] The geographical and economic importance of these institutions for providing credit to small businesses and consumers is, arguably, vital to the overall health and growth of local economies. By these standards, the reduction and failure of community banks is not merely trivial.

Much of the current literature on US banking focuses on aggregate financial institutions despite the distinct risk profiles between smaller community banks and larger lending institutions (i.e. non-community banks). Lux and Greene (2015) contrast the financial profiles of community and non-community banks, noting that community banks typically have less leverage, less-robust returns, and less of an emphasis on technology. Additionally, community banks are not as intensely involved in the capital or securitization markets, and their earnings streams tend to be less diverse which makes them more vulnerable to economic and financial disruptions. Following the 2007 global financial crisis, material loss reviews by federal bank regulators provided insight into some of the common attributes of failed banks, particularly small community banks. In many instances, failed community banks participated heavily in out-of-area lending and speculative commercial and residential loans. Moreover, these institutions tended to fund such loan growth with brokered deposits and other non-core funding as growth surpassed local funding sources. While these attributes of failed community banks are reasonably persistent across banking crises, they were obviously most acute following the most recent financial crisis.

Given the stark differences in institutional profiles between community and non-community banks and the insights provided by material loss reviews, we hypothesize that bank-specific covariates relating to asset quality and earnings likely have a differential impact on community bank failure risk as compared to non-community bank failure risk. We believe this differential impact likely manifests in areas relating to asset quality and earnings because of the unequivocal differences between community and non-community bank earnings channels and lending practices. A detailed look at how community bank-specific covariates impact failure risk will facilitate a more robust understanding of the niche industry and its unique characteristics.

In order to explore the hypothesis of a differential impact, historical balance sheet and income statement information is retrieved from the FDIC and Federal

[2] Fogel, Raja, and Yeager (2011) show that country-level foreclosure rates are lower for community banks, compared to mortgage brokers and universal banks, in areas where there is a "strong" community bank presence.

Reserve Bank databases. Additionally, the TED spread is incorporated into model specifications to control for macroeconomic shocks via liquidity and credit channels.[3] Survival analysis techniques are employed to estimate the magnitude and significance of the bank-specific and macroeconomic covariates in determining failure rates. Specifically, we adopt the semiparametric Cox Proportional Hazards model and evaluate a sample of failed US community banks relative to a sample of non-failed US community banks over the period 1992 to 2013. In total, we analyze 452 community banks that failed between 2000 and 2013 consisting of 6,350 bank-year observations, and 6,217 non-failed community banks consisting of 124,167 bank-year observations.

Empirical results concerning balance sheet information highlight that smaller community banks (based on total assets) are less likely to fail than their larger community bank counterparts. Unsurprisingly income statement measures show that banks with decreasing income sources and increasing income uses are more likely to fail. Overall, ordinary balance sheet and income statement information in the level form afford some useful insights into failure risk, but demonstrate relatively little economic significance. Of much more relevance to the differential impact hypothesis are financial ratios categorized following the CAMELS rating system. Survival models conditioned on financial ratio covariates provide a significant increase in the predictive ability of community bank failure risk. Much of the ratio findings are consistent with current banking literature in terms of the coefficient sign and, in most instances, the relative magnitude of the parameter estimates; however, two interesting results emerge that validate the differential impact hypothesis. First, when conditioning bank failure on ratios related to asset quality and liquidity, community banks that reduce their proportion of consumer lending as a percentage of total assets have much higher failure rates. Existing literature shows that banks which are fully lent up (i.e. have a high ratio of loans to assets) have higher funding risks, and in fact we validate such findings for other loan-to-asset ratios examined—specifically, commercial and industrial loans and real estate loans. We posit that this differential result regarding consumer lending underscores the importance of community banks' unique knowledge of local market conditions and borrower characteristics. That is, lending practices in this particular market segment are vital to community bank survival because of their distinctive comparative advantage in consumer lending relative to non-community banks.

Second, when conditioning bank failure on earnings ratios, a decrease in salary and wage expenses as a proportion of total assets results in a dramatic increase in community bank failure risk. Generally, wage ratios in excess of peer averages are interpreted as a negative factor in bank performance—that is, excessive salaries and benefits are wasteful. Given the strong relational nature of community banking we surmise that this result is a byproduct of two qualitative factors specific to the

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[3] Cole and Wu (2009) extend their analysis of US bank failure to incorporate macroeconomic components.

community banking industry—excellent management and quality employee retention. Effective managers are vital to the survival of relationship driven community banks, and as such "better" managers require increased compensation for their efforts. Moreover, quality employee retention for community banks is paramount. These institutions strongly rely on a flexible relationship banking paradigm that is only as good as its employees and their networks within the local communities. In order to retain valuable employees and reduce turnover, community banks must appropriately compensate their workforce. Thus, a reduction in salary and wages relative to total assets results in a very strong increase in failure rates.

2. Literature review

Trying to identify why banks fail has been an ongoing issue in the finance literature since the late 1960's. Swicegood and Clark (2001) and Kumar and Ravi (2007) both provide a comprehensive review of the findings and research methodologies employed to try and solve the bankruptcy prediction problem. The surveys assess the strengths and weaknesses of the techniques applied to determine bankruptcy prediction, such as, statistical models, neural networks, case-based reasoning, decision trees, operational research, evolutionary approaches, and soft computing techniques. Kumar and Ravi (2007) emphasize that the most precise way of monitoring the financial condition of banks is via on-site examinations. These examinations are conducted on a bank's properties by official regulators every 12 to 18 months and are required by the FDIC Improvement Act of 1991. Regulators utilize a ratings system known as CAMELS that evaluates the capital adequacy, asset quality, management expertise, earnings strength, liquidity, and market risk sensitivity of financial institutions. Analysis of these components provides the supervisory body with private, imperative information about the financial soundness of banks and allows for the assignment of composite ratings to the institutions ranging from one (strong) to five (deficient). Cole and Gunther (1995) report that, while very important, the CAMELS ratings decay quite rapidly.

Wheelock and Wilson (2000) were early adopters of the survival analysis methodology to investigate bank failure. They implement the Cox Proportional Hazards model with time-varying covariates to analyze commercial bank failure rates over the period 1984 to 1993 and find that poorly capitalized, less liquid, less (managerially) efficient, and less profitable banks are much more likely to fail.[4] They also document that institutions holding more risky asset portfolios have an increased likelihood of failure. Shumway (2001) shows that the dynamic hazard model outperforms the more traditional bankruptcy models, and that a hazard model which combines both accounting and market information substantially improves predicting bankruptcy. Though the work of Shumway (2001) focused on US corporate

[4] A few early studies implement the hazard framework pertaining to predictive bank failure; however, they use relatively small samples and short horizon periods (see Lane, Looney, and Wansley, 1986; Whalen, 1991).

bankruptcies, he comprehensively demonstrates that a dynamic hazard model provides more consistent in-sample estimations and more accurate out-of-sample predictions. Beaver, McNichols, and Rhie (2005) extend the work of Shumway (2001) and show that there is a slight decline in the predictive ability of financial ratios, but it can be compensated for by adding market variables into hazard estimation.

More recently, Cole and Wu (2009) compare the forecasting accuracy of the dynamic hazard model using both bank-specific and macroeconomic variables on a large sample of US commercial banks. They find that relative to a static probit model the hazard model significantly improves the accuracy of failure forecasting. Moreover, they find evidence that declining economic growth contributes to the failure of banks with high non-performing loans and shocks to interest rates make banks heavily relying on long-term borrowing more susceptible to failure.

Alali and Romero (2013) use survival analysis to determine how early the indicators of bank failure can be observed. Utilizing a large sample of US commercial banks that failed between 2000 and 2012, they find that older banks and banks with high real estate and agricultural loans, loan charge-offs, loan loss allowances, and non-performing loan-to-asset ratios are more likely to fail. Curiously, they also note that banks with high loan-to-asset ratios are more likely to survive. Pappas, Ongena, Izzeldin, and Fuertes (2013) undertake a similar analysis for international banking. They estimate the conditional hazard rates for both Islamic and conventional banks from 20 Middle and Far East countries and report that Islamic banks have significantly lower risk of failure both unconditionally and conditionally on time-varying bank-specific and macroeconomic covariates. They emphasize that the implementation of early warning systems of bank failure should recognize the distinct risk profiles of the two diverse institutions.

Our research complements this line of literature on bank failure prediction. We employ survival analysis, and in particular the Cox Proportional Hazards model, to investigate the effects of bank-specific covariates on community bank failure. We feel that the distinct risk profiles of community and non-community banks merits further investigation into the differential impact of specific covariates on community bank failure rates. To this end, we utilize a broad set of balance sheet and income statement information to determine the unique impact of bank-specific indicators on failure risk.

3. Methodology

3.1. Community banking definition and data sample

In order to analyze the community banking industry in the US it is first necessary to define what it means to be a community bank. In general, a rough agreement exists on the characteristics that define a community bank as most of the attributes encompass how and where a community bank conducts its business practices. For instance, community banks primarily focus on traditional banking services in their local communities where they obtain the majority of their core deposits and provide the lion’s share of their loans to small businesses and local consumers. This form of banking practice is often referred to as "relationship" lending and borrowing (as opposed to "transactional") since the small institutions have a specialized knowledge of their local community and customers.[5] This expertise allows community banks to base their lending decisions on unique local knowledge and non-standard long-term relationship data rather than customary underwriting models alone, which are typically implemented by large-scale institutions.

While there is a general consensus about the characteristics that make up community banks, formally defining them has been a more difficult task. What exactly constitutes small, basic banking activities is both subjective and difficult to measure; most regulators and practitioners cannot even fully agree on what defines a community bank. In fact, the three largest banking regulators: the Office of the Comptroller of Currency (OCC), the Federal Reserve Board (FRB), and the FDIC all use a different definition for community banks. The OCC defines a community bank as any banking institution with $1 billion in total assets or less. The FRB uses a higher total asset threshold of $10 billion or less as their community bank designation. The FDIC changed their definition of community banks in 2012 to establish standard requirements for lending, deposit gathering, and geographic scope of operations that an institution must meet to be designated as a community bank. This new classification scheme is loosely based on the $1 billion size criteria the FDIC previously utilized, but goes beyond the standard approach of total assets in separating community from non-community banks.[6] The standard methodology used in academia to define community banks has typically been by the size threshold, and has ranged anywhere from $750 million to $10 billion; the size condition alone may be an imperfect metric and seem rather arbitrary, but numerous studies use $1 billion in total assets as an approximate limit.[7] In this study, we define a community bank as a state- or federally-chartered institution that has $1 billion in inflation-adjusted total assets or less. The nominal total asset values for the full sample of banks are adjusted into 2013 constant-dollars using the CPI-U measure of inflation reported by the Bureau of Labor Statistics (BLS). The total asset values are adjusted because it is essential that any dollar-based yardstick evolve over time to account for inflation, economic growth, and changes in the size of the banking industry.

We collect FDIC year-end bank data for all US banking institutions that are FDIC insured in the Statistics and Depository Institutions (SDI) database. The SDI database collects financial data for nearly 1,000 different variables for all FDIC insured state- and federally-chartered banks. The database includes information from income statements, balance sheets, and other sources pertaining to derivatives and risky assets. We obtain an indicator of US macroeconomic conditions, the TED

[5] Hein, Koch, and MacDonald (2005) provide more information on the practice of "relationship" banking.
[6] See the FDIC Community Banking Study (December, 2012) for specific criteria.
[7] DeYoung, Hunter, and Udell (2004), Hassan and Hippler (2014), the FDIC, and the OCC apply the $1 billion limit.

spread, from the Federal Reserve Bank of St. Louis. The TED spread is defined as the percentage difference between interest rates on interbank loans and short-term US government debt. Specifically, it is the difference between the three-month LIBOR and the three-month T-bill interest rates, and is an indicator of interbank credit and liquidity risk. Overall, it functions as a useful gauge for the perceived health of the banking system. A rising (falling) TED spread indicates a decrease (increase) in market liquidity and an increase (decrease) in the risk of default rates, particularly for non-performing loans, and is a sign that lenders believe the risk of default on interbank loans is increasing (decreasing). During crises the interbank lending market does not function smoothly and any shock to interest rates can make banks that heavily rely on long-term borrowing much more vulnerable to failure.[8]

First, we apply our definition of a community bank to a sample of 516 US banking institutions from the "FDIC Failed Banks List" that failed between the period January 2000 and December 2013 and have at least three years of institutional data. This list includes banks that failed and were subsequently acquired by another institution and banks that failed and were left unacquired.[9] A complicating issue is that some failed community banks grow beyond the $1 billion inflation-adjusted asset threshold during some years of the study. In order to remove the banks that have clearly outgrown the community bank definition through time we analyze the sample and remove the institutions that are above the size threshold during at least one of the last five years of available institutional data and continue to remain above the size breakpoint thereafter. Finally, we winzorize the right-tail of the failed banks group at the 0.5 percent level when sorted on total assets in order to remove banks that jumped far above the size criteria in the final year of the sample.[10] The results of this procedure yield a total of 452 failed community banks and 6,350 bank-year observations.

Next, we apply our definition of a community bank to a sample of 9,350 non-failed US banking institutions from the FDIC database that have data from January 1992 (when data is first available) or since the institutions inception through December 2013. We apply the same filtering procedure used on the failed banks data sample except that we winzorize the right-tail of the non-failed banks group at the one percent level when sorted on total assets to remove the institutions that grew far

[8] Through 2006 and into the second quarter of 2007 the TED spread remained steadfast around 50 basis points; however, in August of 2007 the spread began to widen, reaching over 200 basis points in November 2007 (a year before the collapse of Lehman Brothers) and peaking at 315 basis points in September 2008. The TED spread remained elevated through year-end 2008, averaging nearly 150 basis points.

[9] Of the 516 failed US banks, 485 were acquired by other institutions and 31 were not acquired at all. There were 255 unique acquirers, and of those 167 made single bank acquisitions, while the rest (88) made multiple bank acquisitions (which accounted for approximately 3.6 acquisitions on average).

[10] We subsequently apply another filter where community banks missing return on equity (ROE) and return on assets (ROA) data are removed from the sample of failed community banks. However, none of the 452 community banks failed this filtering process.

beyond the asset threshold in the last year of the sample. Additionally, we remove banks that do not have ROE and ROA data reported.[11] The results of this procedure yield a total of 6,217 non-failed community banks and 124,167 bank-year observations. The combined sample of failed and non-failed community banks results in a total of 6,669 subjects and 130,517 bank-year observations. This comprehensive dataset allows for a thorough, retrospective examination of failed community banks relative to non-failed community banks.

3.2. Variable selection

We apply balance sheet and income statement variables as bank failure predictors both in the level form and as financial ratios categorized following the CAMELS rating system. Market-based models have found that stock return and volatility data are very useful in failure studies (see Pettaway and Sinkey, 1980; Curry, Elmer, and Fissel, 2007); however, return data is only available for publicly listed institutions and the universe of community banks are typically private. Fortunately, Pettway and Sinkey (1980) find that accounting information generally leads market prices so that the sole use of accounting information is justifiable.[12]

Regulatory efforts such as the Basel Accords that are aimed at safeguarding the financial stability of banks hinge on the supposition that capital and liquidity regulations make banks more resilient to shocks from the real economy. Kaplan and Camelia (2013) highlight the role of balance sheet strength in the transmission between financial sector shocks and the real economy, noting that banks with strong balance sheets were better able to maintain lending during the 2007 financial crisis. Cole and Gunther (1995) find capital and troubled assets to be among the most important variables in explaining the timing of bank failure. Similarly, a careful review of a bank's income statements will reveal key factors about the institution's financial condition. In fact, Cole and Gunther (1995) find net income to be a vitally important element of bank failure risk. We parse the literature on bank failure to see what prior work has validated as useful predictors of bank failure and include those in our pool of relevant covariates. Most importantly, we include several measures of asset quality and earnings that we believe highlight the fact that community banks have a unique informational advantage in lending, are not as intensely involved in the securitization markets, and have less diverse earnings streams relative to non-community banks. Pertinent balance sheet information regarding bank stability includes the following: total assets (Asset), total liabilities (Liab), total equity capital (Eqtot), tier-one core capital (Riskcapt1), commercial and industrial loans (Loanci), loans to individuals (Loancon), real estate loans (Loanre), farm loans (Loanag), and total loans and leases (Loanlease).[13] The income statement information includes: total

[11] The ROE and ROA criterion results in the removal of only four community banks from the sample.
[12] Explicit management ratios are also excluded from this study due to data unavailability.
[13] We consider farm loans (Loanag) and its accompanying ratios in our initial analysis, but it is excluded from our final results due to missing observations for many institutions.

interest income (Intinc), income before extraordinary items (Incext), total interest expense (Intexp), total non-interest expense (Nonintinc), net income (Netinc), net operating income (Netopinc), and provisions for loan and lease losses (LLLP).

Prior work by Wheelock and Wilson (2000), Cole and Wu (2009), Bell (1997), and Alali and Romero (2013) find pronounced success analyzing financial ratios as predictors of bank failure. We similarly attempt to capture the value of these ratios pertaining to community bank failure by analyzing three categories of the CAMELS rating system: capital adequacy, asset quality and liquidity, and earnings. We include the following capital adequacy ratios: total equity capital to total assets (Eq_Asset), total equity capital to total loans and leases (Eq_Loanlease), and total equity capital to risk-weighted adjusted assets (Eq_RWA). The asset quality and liquidity ratios include: commercial and industrial loans to total assets (Loanci_Asset), loans to individuals to total assets (Loancon_Asset), real estate loans to total assets (Loanre_Asset), farm loans to total assets (Loanag_Asset), total loans and leases to total assets (Loanlease_Asset), loss allowances to total assets (Lossallow_Asset), net charge-offs to total assets (Chargeoff_Asset), total loan and lease loss provisions to total assets (LLLP_Asset), loss allowance to total loans and leases (LLLP_Loanlease), net charge-offs to total loans and leases (Chargeoff_Loanlease), total loans and leases to total deposits (Loanlease_Dep), and tier-one capital to risk-weighted assets (Riskcapt1_RWA). Finally, the earnings ratios include: income before extraordinary items to total assets (Incext_Asset), net operating income to total assets (Netopinc_Asset), net interest margin (Netint_Asset), salary and wage expenses to total assets (Wage_Asset), return on assets (ROA), and return on equity (ROE).

We further extend the analysis by incorporating the macroeconomic TED spread covariate (Ted_Spread) into our specifications to control for macroeconomic shocks and their contribution to community bank failure.[14] Table 1 provides an extensive definition of all variables.

3.3. *Research design*

We apply the survival analysis methodology to our community bank failure investigation rather than the more traditional models of binary logit or ordinary least squares (OLS). Survival models can accommodate both lifetime and censored data. More importantly, these models overcome the pitfall of assumed normality, which is the true drawback to the linear regression framework. The distributions for time to an event (i.e. community bank failure) are likely disparate from the commonly assu-

[14] Arena (2008) studies the 1990's Latin America and East Asia banking crises and notes that individual bank conditions explain bank failures, while macroeconomic shocks (which triggered the crises) primarily destabilized the weaker banks.

Table 1. Dependent and Conditioning Variables.

Variables	Symbol	Type	Definition
Dependent			
Bank Failure	Bank_Fail	Qualitative	Binary indicator variable which is equal to one for failed banks in the year that they fail and zero in all preceding years. The variable is equal to zero in all sample years for surviving banks.
Independent			
Total Assets	Asset	Balance Sheet	The sum of all assets owned by the institution including cash, loans, securities, bank premises and other assets. This total does not include off-balance-sheet accounts.
Total Liabilities	Liab	Balance Sheet	Deposits and other borrowings, subordinated notes and debentures, limited-life preferred stock and related surplus, trading account liabilities and mortgage indebtedness.
Total Equity Capital	Eqtot	Balance Sheet	Total equity capital on a consolidated basis.
Tier-one (core) Capital	Riskcapt1	Balance Sheet	Tier-one (core) capital includes: common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. The amount of eligible intangibles (including mortgage servicing rights) included in core capital is limited in accordance with supervisory capital regulations.
Commercial and Industrial Loans	Loanci	Balance Sheet	Loans for commercial and industrial uses, excluding: all loans secured by real estate, loans to individuals, loans to depository institutions and foreign governments, loans to states and political subdivisions and lease financing receivables.
Loans to Individuals	Loancon	Balance Sheet	Loans to individuals for household, family, and other personal expenditures including outstanding credit card balances and other secured and unsecured consumer loans.
All Real Estate Loans	Loanre	Balance Sheet	Loans secured primarily by real estate, whether originated by the bank or purchased.
Farm Loans	Loanag	Balance Sheet	Loans to finance agricultural production and other loans to farmers, excluding savings institutions filing a Thrift Financial Report.
Total Loans and Leases	Loanlease	Balance Sheet	Total loans and lease financing receivables, net of unearned income.

Table 1. Dependent and Conditioning Variables.

Variables	Symbol	Type	Definition
Total Interest Income	Intinc	Income Statement	Sum of income on loans and leases, plus investment income, interest on interest bearing bank balances, interest on federal funds sold and interest on trading account assets earned by the institution.
Income before Extraordinary Items	Incext	Income Statement	Income (loss) before security transactions, extraordinary items and other adjustments.
Total Interest Expense	Intexp	Income Statement	Total interest expenses.
Total Non-interest Income	Nonintinc	Income Statement	Income from fiduciary activities, plus service charges on deposit accounts in domestic offices, plus trading gains (losses) and fees from foreign exchange transactions, plus other foreign transaction gains (losses), plus other gains (losses) and fees from trading assets and liabilities.
Net Income	Netinc	Income Statement	Net interest income plus total noninterest income plus realized gains (losses) on securities and extraordinary items, less total noninterest expense, loan loss provisions and income taxes.
Net Operating Income	Netopinc	Income Statement	Net income excluding discretionary transactions such as gains (losses) on the sale of investment securities and extraordinary items. Income taxes subtracted from operating income have been adjusted to exclude the portion applicable to securities gains (losses).
Provisions for Loan and Lease Losses	LLLP	Income Statement	The amount needed to make the allowance for loan and lease losses adequate to absorb expected loan and lease losses (based upon management's evaluation of the bank's current loan and lease portfolio).
Total Equity Capital to Total Assets	Eq_Asset	Financial Ratio: Capital Adequacy	Total equity capital as a percent of total assets.
Total Equity Capital to Total Loans and Leases	Eq_Loanlease	Financial Ratio: Capital Adequacy	Total equity capital as a percent of total loans and lease financing receivables, net of unearned income.
Total Equity to Risk-Weighted Adjusted Assets	Eq_RWA	Financial Ratio: Capital Adequacy	Total equity capital to total risk-weighted adjusted assets. Risk-weighted assets are adjusted for risk-based capital definitions which include on-balance-sheet as well as off-balance-sheet items multiplied by risk-weights that range from zero to 200 percent.

Table 1. Dependent and Conditioning Variables.

Variables	Symbol	Type	Definition
Commercial and Industrial Loans to Total Assets	Loanci_Asset	Financial Ratio: Asset Quality and Liquidity	Commercial and industrial loans as a percent of total assets.
Loans to Individuals to Total Assets	Loancon_Asset	Financial Ratio: Asset Quality and Liquidity	Loans to individuals as a percent of total assets.
Real Estate Loans to Total Assets	Loanre_Asset	Financial Ratio: Asset Quality and Liquidity	All real estate loans as a percent of total assets.
Farm Loans to Total Assets	Loanag_Asset	Financial Ratio: Asset Quality and Liquidity	Farm loans as a percent of total assets.
Total Loans and Leases to Total Assets	Loanlease_Asset	Financial Ratio: Asset Quality and Liquidity	Total loans and lease financing receivables, net of unearned income, as a percent of total assets.
Loss Allowance to Total Assets	Lossallow_Asset	Financial Ratio: Asset Quality and Liquidity	Allowance reserve for loan and lease losses that is adequate to absorb estimated credit losses associated with its loan and lease portfolio (which also includes off-balance-sheet credit instruments) as a percent of total assets.
Net Charge-offs to Total Assets	Chargeoff_Asset	Financial Ratio: Asset Quality and Liquidity	Gross loan and lease financing receivable charge-offs, less gross recoveries, (annualized) as a percent of total assets.
Total Loan and Lease Loss Provisions to Total Assets	LLLP_Asset	Financial Ratio: Asset Quality and Liquidity	The annualized provision for loans and lease losses as a percent of total assets on a consolidated basis.
Total Loan and Lease Loss Provisions to Total Loans and Leases	LLLP_Loanlease	Financial Ratio: Asset Quality and Liquidity	Allowance for loan and lease losses as a percent of total loan and lease financing receivables, excluding unearned income.
Total Loans and Leases to Total Deposits	Loanlease_Dep	Financial Ratio: Asset Quality and Liquidity	Total loans and lease financing receivables, net of unearned income, as a percent of the sum of all deposits including demand deposits, money market deposits, other savings deposits, time deposits and deposits in foreign offices.

Table 1. Dependent and Conditioning Variables.

Variables	Symbol	Type	Definition
Net Charge-offs to Total Loans and Leases	Chargeoff_Loanlease	Financial Ratio: Asset Quality and Liquidity	Total loans and leases charged-off (removed from balance sheet because of uncollectibility), less amounts recovered on loans and leases previously charged-off as a percent of total loans and lease financing receivables.
Tier-one Capital to Risk-Weighted Adjusted Assets	Riskcapt1_RWA	Financial Ratio: Asset Quality and Liquidity	Tier-one (core) capital as a percent of risk-weighted assets as defined by the appropriate federal regulator for prompt corrective action during that time period.
Income before Extraordinary Items to Total Assets	Incext_Asset	Financial Ratio: Earnings	Income before extraordinary items as a percent of total assets.
Net Operating Income to Total Assets	Netopinc_Asset	Financial Ratio: Earnings	Net operating income (annualized) as a percent of average total assets.
Net Interest Margin to Total Assets	Netint_Asset	Financial Ratio: Earnings	Total interest income less total interest expense (annualized) as a percent of average total earning assets.
Salary and Wage Expenses to Total Assets	Wage_Asset	Financial Ratio: Earnings	Salary and employee benefit expenses as a percent of total assets.
Return on Assets	ROA	Financial Ratio: Earnings	Net income after taxes and extraordinary items (annualized) as a percent of average total assets.
Return on Equity	ROE	Financial Ratio: Earnings	Annualized net income as a percent of average equity on a consolidated basis.
TED Spread	Ted_Spread	Macroeconomic	The difference between the three-month LIBOR and the three-month T-bill interest rate.

Note. This table presents all dependent and independent variable definitions. All financial variable data and definitions are obtained from the FDIC database. Macroeconomic data is obtained from the Federal Reserve Bank of St. Louis.

med normality and are undoubtedly non-symmetric. A linear regression framework is not robust to these types of violations. Survival analysis models on the other hand can provide proper estimates of expected time to failure and relevant parameter covariates by substituting a more reasonable distribution assumption (e.g. Weibull, exponential, etc.) in the case of parametric modeling, or making no distributional assumptions at all in the case of semiparametric and nonparametric modeling.[15] Survival models of bank failure naturally control for the condition that the number of observation periods of a given bank may not represent the bank's entire lifespan—this is censoring.[16] Of particular relevance is right-censoring; this means that a subject is under study for some period of time and later is no longer observed. In the context of community bank failure, it is entirely plausible a bank could remain in business beyond the conclusion of the sample period and fail at some point in time afterwards. In fact, our entire sample of non-failed community banks represent right-censored observations. Fortunately, the likelihood function can be easily expressed in the presence of right-censoring to account for such data.[17] We adopt the semiparametric Cox Proportional Hazards model (of Cox, 1972) in addressing the issue of community bank failure risk because it alleviates the need for any assumptions about the distribution of failure times. Time plays no significant role other than ordering the observations; however, the semiparametric model does make an assumption about how each subject's observed covariate value determines the probability that a subject would fail. In effect, one is parameterizing the effect of the covariate(s), so that a parametric component of the analysis still exists.

To provide context to the survivor analysis methodology let us denote T as the time to failure event, where $T \epsilon [0, \infty)$, $F(t)$ as its cumulative distribution function, where $F(t) = \Pr(T \leq t)$, and $f(t)$ as its probability density function, where $f(t) = \frac{-dF(t)}{dt}$. In survival analysis it is far more convenient to describe the probability distribution for T in terms of $S(t)$, the survivor function, and $h(t)$, the hazard function, rather than $F(t)$ and $f(t)$, respectively. The survivor function is merely the reverse cumulative distribution function of T, and is given by:

$$S(t) = 1 - F(t) = \Pr(T > t) \qquad (1)$$

The survivor function gives the probability of surviving beyond time t. In other words, it is the probability that there is no failure prior to time t. At $t = 0$ the function is equal to one and subsequently decreases as t approaches infinity. Alternatively, the hazard function, or conditional failure rate, gives the instantaneous rate of failure. The function is given by:

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[15] Nonparametric methods include those of Kaplan and Meier (1958), Nelson (1972), and Aalen (1978).

[16] For a more complete and detailed discussion of survival analysis and its properties see Cleves, Gutierrez, Gould, and Marchenko (2010), Kalbfleisch and Prentice (2002), and Nelson (1972).

[17] In the case of semiparametric models, if subject i is censored at time t_i, then that particular subject enters all the individual failure-time studies up to and including time t_i, and after that is merely ignored.

$$h(t) = \lim_{\Delta t \to 0} \frac{Pr(t + \Delta t > T > t | T > t)}{\Delta t} = \frac{f(t)}{S(t)} \quad (2)$$

The hazard function is the probability of failure occurring within time t, conditional upon the subject having survived to the beginning of time t, divided by the width of the interval. The hazard rate can vary from zero (no risk) to infinity (certain instantaneous failure) and provides the rate at which risk is accumulated given the one-to-one relationship between the probability of surviving past a certain time and the amount of risk that has been accumulated up to that particular time.

The Cox Proportional Hazards model is formalized as:

$$h(t|x_i) = h_0(t)\, exp(x_i \beta_x) \quad (3)$$

where, $h_0(t)$ is the baseline hazard function, x_i is a row vector of covariates, and β_x is a column vector of regression coefficients to be estimated. The beauty of the Cox (1972) model is that $h_0(t)$ is given no particular parameterization as the baseline hazard is left unestimated altogether. Since semiparamteric analysis is confined to only those times that failure occurs, the baseline hazard drops out from calculation.[18] The model makes no assumption about the shape of the baseline hazard function and is the same for all subject's—that is, the hazard for one subject is merely a multiplicative replica of another subject's. The model also assumes the covariates multiplicatively shift the baseline hazard function. Comparing subject i to subject j, the model states that:

$$\frac{h(t|x_i)}{h(t|x_j)} = \frac{exp(x_i \beta_x)}{exp(x_j \beta_x)} \quad (4)$$

where, the covariates x_i and x_j do not change over time. Furthermore, the Cox model assumes the hazard rate increases linearly with time conditional on the covariate(s). In our context the covariates consist of balance sheet, income statement, financial ratio, and macroeconomic information. In order to estimate the time-dependent covariate coefficients we de-mean the lagged variables so that the baseline hazard rate, $h_0(t)$, can be interpreted as the rate of an average bank in the population sample. A value of $\widehat{\beta_x}$ greater (less) than zero indicates that a rise in the x^{th} covariate increases (decreases) failure risk and decreases (increases) survival time. Our covariate selection process is based on a general-to-specific procedure as outlined in Pappas et al. (2013).[19]

We employ the exact-marginal (continuous-time) calculation method for tied failure events in our maximum likelihood calculations. Tied failure events refer to

[18] For a detailed and technical treatment of how this occurs see Kalbfleisch and Prentice (2002).

[19] Pappas et al. (2013) build on the work of Lane et al. (1986), utilizing a forward-and-backward variable selection procedure. The name refers to the fact that the technique can both drop and add covariates sequentially. For each full set of M bank-specific and macroeconomic variables we compare the M regressors and M-1 regressor models and retain the appropriate model based on the following: (1) the significance of the covariates based on the P-values, (2) the likelihood ratio which tests whether $\beta_x = 0$, (3) the Akaike Information Criteria (AIC), (4) the degrees-of-freedom-adjusted Bayesian Information Criterion (BIC), and (5) the log likelihood ratio best-fit criterion.

community banks that failed during the same day and month. This method assumes that the institutions that failed simultaneously did not all fail at the exact same time, but that we are merely limited by how precisely we can measure failure time. In fact, the exact-marginal calculation uses conditional probabilities of tied failures in the maximum likelihood calculations and assumes continuous time so that it is mathematically impossible for bank failures to occur at precisely the same instant.[20]

4. Empirical results

4.1. Descriptive statistics

Table 2 provides the summary statistics of the covariates. Panel A shows the summary information for the failed community bank sample and Panel B for the non-failed community bank sample. The mean, median, standard deviation, minimum, maximum, number of observations, and unit of measurement are reported for each covariate. Further, the summary information for each panel is reported by the following categories: balance sheet, income statement, financial ratio, and macroeconomic. The financial ratio section is further sub-divided into the CAMELS categorizations of capital adequacy, asset quality and liquidity, and earnings.

Comparing panels, the average size (Asset) of a failed community bank ($178.03 million) is slightly larger than a non-failed community bank ($143.24 million). Of particular interest are the covariates related to asset quality and earnings given our belief that a differential impact on community bank failure will come through covariates in these areas. Seemingly little differences exist between failed and non-failed community banks regarding commercial and industrial loans (Loanci), consumer loans (Loancon), and agricultural loans (Loanag). Average real estate loans (Loanre) on the other hand are markedly larger for failed banks ($106.68 million) than non-failed banks ($67.68 million). This latter finding is perhaps owing to the 2007 global financial crisis. Income statement information between failed and non-failed banks show large discrepancies between income before extraordinary items (Incext), net income (Netinc), net operating income (Netopinc), as well as loss provisioning (LLLP). In fact, all income-based measures are negative for failed institutions, though this comes as little surprise since failed community banks are expected to be strikingly less profitable than non-failed community banks.

Financial ratios pertaining to capital adequacy tend to be larger on average for non-failed community banks than failed community banks; however, this type of pattern is not so evident with the ratios relating to asset quality and liquidity. An overview of the earnings ratios shows much poorer performance by the failed banks group. This is consistent with the subpar income statement figures reported for the failed banks in Panel A. In fact, similar to Panel A, all earnings ratios, with the exception of net interest margin to total assets (Netint_Asset) and salary and wage expenses to total assets (Wage_Asset), yield a negative mean value. The largest earni-

[20] Kalbfleisch and Prentice (2002) provide a technical treatment of the marginal calculation method.

Table 2. Summary Statistics for Conditioning Variables by Group.

Variables	Units	Mean	Median	Std. Dev.	Min.	Max.	Obs.
Panel A: Failed Banks							
Balance Sheet							
Asset	$M	178,025.18	106,741.00	204,705.12	1,755.00	1,957,120.00	6,350
Liab	$M	163,746.30	98,424.00	190,032.35	96.00	1,822,604.00	6,350
Eqtot	$M	14,278.88	8,452.00	18,382.19	-47,041.00	209,684.00	6,350
Riskcapt1	$M	13,707.81	8,214.00	17,486.31	-45,673.00	209,518.00	6,350
Loanci	$M	16,230.30	8,093.50	27,579.79	0.00	637,180.00	6,350
Loancon	$M	5,354.14	2,442.50	22,511.16	0.00	856,815.00	6,350
Loanre	$M	106,675.27	55,852.00	141,868.31	0.00	1,491,289.00	6,350
Loanag	$M	1,554.36	0.00	5,686.34	0.00	86,218.00	5,606
Loanlease	$M	130,879.60	73,545.50	162,044.60	0.00	1,639,110.00	6,350
Income Statement							
Intinc	$M	10,654.46	6,155.00	14,198.21	2.00	278,482.00	6,350
Incext	$M	-901.32	377.50	8,469.10	-165,024.00	49,809.00	6,350
Intexp	$M	4,621.63	2,576.00	5,925.42	0.00	63,034.00	6,350
Nonintinc	$M	1,308.45	474.50	4,274.97	-16,357.00	104,142.00	6,350
Netinc	$M	-895.95	384.00	8,489.81	-165,024.00	51,478.00	6,350
Netopinc	$M	-897.15	355.25	8,329.74	-154,895.27	49,709.00	6,350
LLLP	$M	2,246.03	295.00	7,994.67	-5,955.00	206,150.00	6,350
Financial Ratio							
Capital Adequacy							
Eq_Asset	%	9.85	8.60	8.20	-13.51	94.69	6,350
Eq_Loanlease	%	29.10	12.25	592.76	-6,763.20	44,854.54	6,341
Eq_RWA	%	16.45	11.74	52.16	-18.95	3,424.91	6,350
Asset Quality and Liquidity							
Loanci_Asset	%	9.79	7.79	8.53	0.00	73.91	6,350
Loancon_Asset	%	4.28	2.38	5.85	0.00	96.75	6,350
Loanre_Asset	%	52.33	54.98	19.82	0.00	105.44	6,350
Loanag_Asset	%	1.91	0.00	5.52	0.00	65.55	5,606
Loanlease_Asset	%	68.72	71.49	15.58	0.00	97.88	6,350
Lossallow_Asset	%	1.28	0.94	1.19	0.00	20.06	6,350
Chargeoff_Asset	%	0.62	0.10	1.52	-2.01	37.84	6,350
LLLP_Asset	%	0.87	0.29	1.72	-2.09	23.95	6,350

Table 2. Summary Statistics for Conditioning Variables by Group.

Variables	Units	Mean	Median	Std. Dev.	Min.	Max.	Obs.
LLLP_Loanlease	%	1.90	1.34	2.12	0.00	100.00	6,341
Chargeoff_Loanlease	%	1.72	0.50	3.61	-9.89	78.63	6,342
Loanlease_Dep	%	82.99	83.51	31.58	0.00	1,705.65	6,345
Riskcapt1_RWA	%	16.02	11.32	52.11	-19.77	3,424.91	6,350
Earnings							
Incext_Asset	%	-0.34	0.62	2.74	-27.48	7.94	6,350
Netopinc_Asset	%	-0.45	0.69	3.44	-79.48	9.94	6,350
Netint_Asset	%	4.16	4.16	1.84	-9.44	71.25	6,350
Wage_Asset	%	1.74	1.61	0.87	-0.30	14.83	6,350
ROA	%	-0.44	0.72	3.47	-79.48	9.76	6,350
ROE	%	-19.28	7.19	301.29	-11,095.83	6,375.35	6,350
Macroeconomic							
TED_Spread	%	0.56	0.47	0.34	0.15	1.55	6,350
Panel B: Non-Failed Banks							
Balance Sheet							
Asset	$M	143,238.01	87,636.00	160,095.73	19.00	1,703,388.00	124,167
Liab	$M	128,821.67	77,985.00	167,193.46	0.00	14,264,000.00	124,167
Eqtot	$M	15,168.27	9,179.00	18,514.80	-2,984.00	825,213.00	124,167
Riskcapt1	$M	14,611.79	8,945.00	21,641.03	-5,468.00	2,325,000.00	124,167
Loanci	$M	12,072.33	5,168.00	24,017.34	0.00	1,874,000.00	124,167
Loancon	$M	6,845.09	3,364.00	15,757.46	0.00	1,479,739.00	124,157
Loanre	$M	67,675.97	33,606.00	108,975.01	0.00	9,783,000.00	124,167
Loanag	$M	4,601.09	1,203.00	10,067.12	0.00	383,488.00	113,339
Loanlease	$M	91,499.52	52,059.00	111,338.70	0.00	1,515,332.00	124,167
Income Statement							
Intinc	$M	7,948.79	5,106.00	8,729.40	0.00	305,089.00	124,145
Incext	$M	1,241.14	735.00	3,965.55	-351,282.00	439,941.00	124,167
Intexp	$M	2,875.00	1,730.00	3,434.55	-2.00	61,622.00	124,145
Nonintinc	$M	1,407.00	445.00	8,913.32	-120,461.00	909,750.00	124,167
Netinc	$M	1,240.86	737.00	3,964.31	-351,282.00	439,941.00	124,167
Netopinc	$M	1,205.23	716.12	3,944.46	-351,375.72	439,941.00	124,167
LLLP	$M	510.99	106.00	2,974.48	-12,198.00	370,000.00	124,167

Table 2. Summary Statistics for Conditioning Variables by Group.

Variables	Units	Mean	Median	Std. Dev.	Min.	Max.	Obs.
Financial Ratio							
Capital Adequacy							
Eq_Asset	%	12.64	10.02	101.59	-3.60	15,242.01	124,167
Eq_Loanlease	%	80.48	16.69	4,097.26	-4,399.33	758,448.29	123,563
Eq_RWA	%	21.64	15.91	114.09	-5.92	19,094.34	124,167
Asset Quality and Liquidity							
Loanci_Asset	%	20.12	6.60	983.39	0.00	111,481.26	124,167
Loancon_Asset	%	5.94	4.39	6.55	0.00	282.93	124,157
Loanre_Asset	%	97.44	39.74	4,681.42	0.00	581,975.00	124,167
Loanag_Asset	%	5.78	1.55	8.73	0.00	73.61	113,339
Loanlease_Asset	%	61.24	62.28	67.53	0.00	8,347.96	124,167
Lossallow_Asset	%	56.93	0.79	4,613.32	0.00	574,360.50	124,167
Chargeoff_Asset	%	0.24	0.07	5.55	-6.86	1,742.11	124,167
LLLP_Asset	%	2.68	0.13	194.91	-25.42	22,010.71	124,167
LLLP_Loanlease	%	1.49	1.30	12.26	-4,285.71	96.82	123,584
Chargeoff_Loanlease	%	1.17	0.35	3.32	-27.44	470.44	123,614
Loanlease_Dep	%	74.84	73.20	335.77	0.00	107,033.34	124,123
Riskcapt1_RWA	%	20.99	15.40	111.62	-13.52	18,544.72	124,167
Earnings							
Incext_Asset	%	1.09	0.95	24.49	-3,471.04	3,254.80	124,167
Netopinc_Asset	%	0.91	0.99	2.51	-138.19	272.36	124,167
Netint_Asset	%	4.12	4.08	1.36	-166.67	72.64	124,164
Wage_Asset	%	3.57	1.54	151.95	0.00	17,489.59	124,167
ROA	%	0.94	1.01	2.50	-138.19	272.36	124,167
ROE	%	8.90	9.38	41.76	-1,132.20	14,089.74	124,167
Macroeconomic							
Ted_Spread	%	0.51	0.41	0.32	0.19	1.55	124,167

Note. This table presents the summary statistics of the community bank balance sheet, income statement, financial ratio, and macroeconomic variables. Panel A reports the units of measurement, mean, median, standard deviation, minimum, maximum, and number of observations, respectively, for failed community banks over the period 1992 to 2013. Panel B reports the units of measurement, mean, median, standard deviation, minimum, maximum, and number of observations, respectively, for non-failed community banks over the period 1992 to 2013.

Table 3. Univariate Difference-in-Means Tests of Conditioning Variables between Failed and Non-Failed Community Banks.

	Failed Banks (452 Banks)		Non-Failed Banks (6,217 Banks)		
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean Diff.
Balance Sheet					
Asset	178,025.18	204,705.12	143,238.01	160,095.73	34,787.17***
Liab	163,746.30	190,032.35	128,821.67	167,193.46	34,924.63***
Eqtot	14,278.88	18,382.19	15,168.27	18,514.80	-889.39***
Riskcapt1	13,707.81	17,486.31	14,611.79	21,641.03	-903.98***
Loanci	16,230.30	27,579.79	12,072.33	24,017.34	4,157.97***
Loancon	5,354.14	22,511.16	6,845.09	15,757.46	-1,490.95***
Loanre	106,675.27	141,868.31	67,675.97	108,975.01	38,999.29***
Loanag	1,554.36	5,686.34	4,601.09	10,067.12	-3,046.74***
Loanlease	130,879.60	162,044.60	91,499.52	111,338.70	39,380.12***
Income Statement					
Intinc	10,654.46	14,198.21	7,948.79	8,729.40	2,705.67***
Incext	-901.32	8,469.10	1,241.14	3,965.55	-2,142.47***
Intexp	4,621.63	5,925.42	2,875.00	3,434.55	1,746.63***
Nonintinc	1,308.45	4,274.97	1,407.00	8,913.32	-98.54
Netinc	-895.95	8,489.81	1,240.86	3,964.31	-2,136.81***
Netopinc	-897.15	8,329.74	1,205.23	3,944.46	-2,102.37***
LLLP	2,246.03	7,994.67	510.99	2,974.48	1,735.04***
Financial Ratio					
Capital Adequacy					
Eq_Asset	9.85	8.20	12.64	101.59	-2.79**
Eq_Loanlease	29.10	592.76	80.48	4,097.26	-51.38
Eq_RWA	16.45	52.16	21.64	114.09	-5.19***
Asset Quality and Liquidity					
Loanci_Asset	9.79	8.53	20.12	983.39	-10.33
Loancon_Asset	4.28	5.85	5.94	6.55	-1.66***
Loanre_Asset	52.33	19.82	97.44	4,681.42	-45.11
Loanag_Asset	1.91	5.52	5.78	8.73	-3.87***
Loanlease_Asset	68.72	15.58	61.24	67.53	7.48***
Lossallow_Asset	1.28	1.19	56.93	4,613.32	-55.66

Table 3. Univariate Difference-in-Means Tests of Conditioning Variables between Failed and Non-Failed Community Banks.

	Failed Banks (452 Banks)		Non-Failed Banks (6,217 Banks)		
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean Diff.
Chargeoff_Asset	0.62	1.52	0.24	5.55	0.38***
LLLP_Asset	0.87	1.72	2.68	194.91	-1.81
LLLP_Loanlease	1.90	2.12	1.49	12.26	0.41***
Chargeoff_Loanlease	1.72	3.61	1.17	3.32	0.55***
Loanlease_Dep	82.99	31.58	74.84	335.77	8.15**
Riskcapt1_RWA	16.02	52.11	20.99	111.62	-4.97***
Earnings					
Incext_Asset	-0.34	2.74	1.09	24.49	-1.44***
Netopinc_Asset	-0.45	3.44	0.91	2.51	-1.36***
Netint_Asset	4.16	1.84	4.12	1.36	0.04**
Wage_Asset	1.74	0.87	3.57	151.95	-1.83
ROA	-0.44	3.47	0.94	2.50	-1.38***
ROE	-19.28	301.29	8.90	41.76	-28.19***
Macroeconomic					
Ted_Spread	0.56	0.34	0.51	0.32	0.05***

Note. This table presents the difference-in-means statistics for the community bank balance sheet, income statement, financial ratio, and macroeconomic variables. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

ngs ratio discrepancy between the two groups is ROE, where the average for failed banks is -19.28 percent, while that of non-failed banks is 8.90 percent.

Table 3 provides the difference-in-means tests for the two groups of conditioning variables in Table 2. Balance sheet information shows that the difference-in-means for failed and non-failed community banks are significant at the one percent level for all tests. Similar results are reported for income statement covariates with the sole exception of non-interest income (Nonintinc). Findings for the three categories of financial ratios are slightly more varied, but the general consensus that the difference-in-means between the failed and non-failed sample of banks are statistically significant remains unchanged.

Overall, the sample statistics provide some very general insights into the nuances of community bank failure. What is strongly validated though is the need for a more technical treatment of the data to determine the role and specific impact of the covariates in relation to failure risk. In the following section we dive deeper into this issue by utilizing the Cox Proportional Hazards model to analyze the differential impact hypothesis.

4.2. Cox proportional hazards regression analysis

First, we estimate separate Cox Proportional Hazards models for the balance sheet and income statement covariates. Next, we estimate separate models for the capital adequacy, asset quality and liquidity, and earnings ratios. Finally, we estimate a comprehensive model that aggregates the most pertinent financial ratios. The separate estimation of the covariates is meant to assess the relevant impact and value-added from the different factors of our diverse and rich information sets in predicting failure. More importantly, the approach allows us to clearly view and interpret any differential impact for a given covariate. While we concede that one would want to utilize as much information as possible in predicting community bank failure, the aforementioned reasons lead us to investigate our hypothesis in this manner.[21] We apply the forward-and-backward selection procedure discussed earlier to arrive at model specifications that yield the most parsimonious and best overall fit of the data.[22] For each regression we report two model specifications. Model I includes bank-specific covariates only and model II includes the same bank-specific covariates from model I and the macroeconomic control variable. The results of this process are reported in Tables 4 through 9.

An overall picture of the US community banking industry is provided in Figure I. It shows the Nelson-Aalen cumulative hazard estimates as a plot of the percentage of failed community banks relative to total community banks over the entire sample period. Overall, approximately 0.07 percent of the community banks

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[21] A "horse race" of different information sets is not our intention, we aim to ascertain valuable practical information from each estimated model.

[22] Correlation matrices are also utilized to help identify the most appropriate covariates for a given model; the correlation matrices are unreported for brevity, but available upon request.

in the sample failed by the end of 2013. Below the x-axis of Figure I are the number of community banks at risk and the number of failed community banks for a given interval (failed banks are listed in parenthesis). For instance, between the years 1998 and 2003 approximately 118 community banks failed while 6,613 were at risk at the beginning of the period. The largest failure rate occurs between 2008 and 2013 with a total of 212 banks succumbing to failure. This obviously coincides with the far-reaching and detrimental effects of the 2007 global financial crisis on the US financial and banking systems.

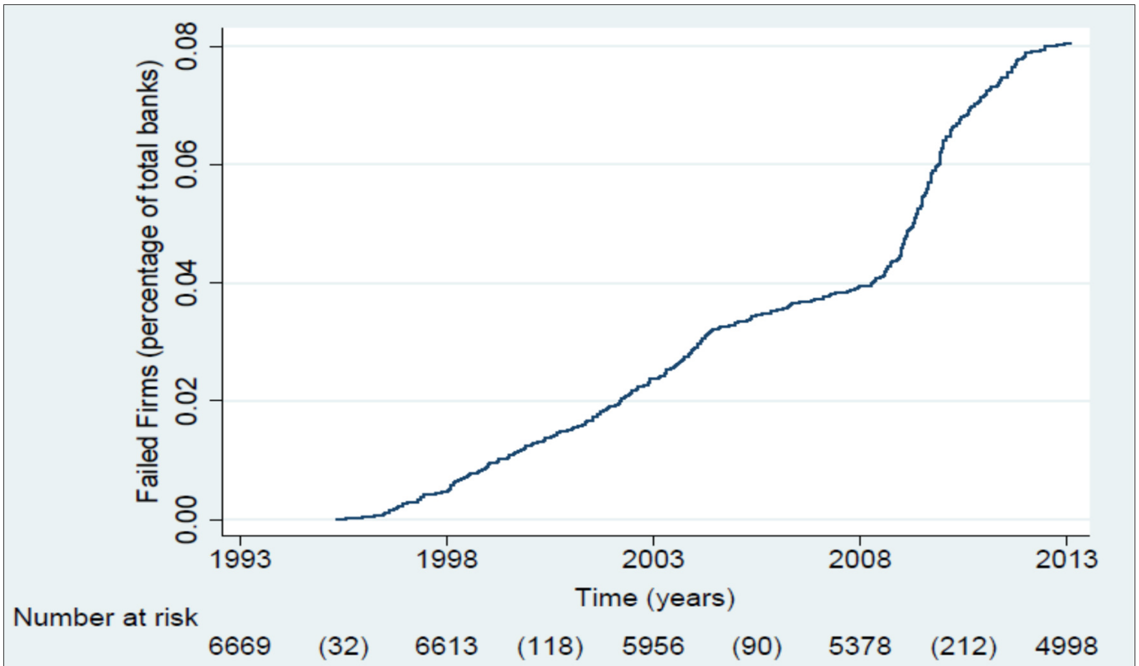

Figure I. Nelson-Aalen Cumulative Hazard Estimates of US Community Banks

Table 4 reports the results of conditioning community bank failure on balance sheet information. Model I shows that the estimated coefficients of all the covariates, except real estate loans (Loanre), are significant at the one percent level. A negative (positive) coefficient indicates that the risk of failure, or the hazard rate, increases—or alternatively, the survival likelihood decreases—as the covariate decreases (increases). For instance, as the level of tier-one core capital (Riskcapt1)—a measure of a bank's financial strength—decreases there is a resultant increase in the rate of failure. The corresponding hazard ratios, or exponentiated coefficients, provide an estimate of the rate of failure for a one-unit increase in the respective covariate. Hazard ratios larger (smaller) than one provide the increase in the rate of failure occurring for a one-unit increase (decrease) in the associated covariate, after controlling for other factors. Due to the small magnitude of the covariate coefficients all of the hazard ratios in the model are very close to one.

The most interesting result of model I is the negative coefficient on bank size (Asset). Despite the small economic magnitude of the coefficient, the sign indicates that larger community banks are relatively more likely to fail than smaller ones. Prior work, such as Wheelock and Wilson (2000) and Cole and Wu (2009), show that in the universe of commercial banks it is generally the smaller institutions that are more likely to fail. This differential result complements the current banking literature in emphasizing that the relation between bank size and failure risk is not necessarily linear. Thus, while community banks may be more susceptible to failure risk relative to non-community banks, the smallest community banks are not automatically the most at risk. This result is likely due in part to the more risk-averse profiles these smaller institutions maintain relative to their larger counterparts. Small community banks typically limit very risky lending practices because of their inability to securitize such loans, and this provides a certain degree of insulation from outside economic shocks. Model II reports the results from including the TED spread (Ted_Spread) as a macroeconomic control. The inclusion of the covariate yields similar results as the bank-specific only model, except that real estate loans (Lonre) is now rendered statistically insignificant. The TED spread is statistically significant

Table 4. Cox Survival Model Conditioned on Balance Sheet and Macroeconomic Covariates.

	Model I Balance Sheet		Model II Balance Sheet & Macro	
Variables	Coef.	Hazard Ratio	Coef.	Hazard Ratio
Asset	0.000006***	1.000006	0.000006***	1.000006
Riskcapt1	-0.000101***	0.999899	-0.000104***	0.999896
Loanci	-0.000008***	0.999992	-0.000009***	0.999991
Loancon	-0.000070***	0.999930	-0.000070***	0.999930
Loanre	0.000002*	1.000002	0.000002	1.000002
Ted_Spread			102.085600***	2.16E+44
Likelihood Ratio	1,334.03***		1,347.72***	
AIC	6,296.17		6,284.47	
BIC	6,330.20		6,325.31	
Log Likelihood	-3,143.09		-3,136.24	
Banks	6,669		6,669	
Failures	452		452	
Obs. (bank-year)	130,507		130,507	

Note. This table presents the Cox regression models based on balance sheet and macroeconomic information. For each full set of M bank-specific and macroeconomic variables we compare the M regressors and M-1 regressor models and retain the appropriate model based on the following: (1) the significance of the covariates based on the P-values, (2) the likelihood ratio which tests whether $\beta_x=0$, (3) the Akaike Information Criteria (AIC), (4) the degrees-of-freedom-adjusted Bayesian Information Criterion (BIC), and (5) the log likelihood ratio best-fit criterion. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

at the one percent level and is of high economic significance relative to the much smaller bank-specific coefficients. The correspondingly large hazard ratio highlights the strong linkage between community bank failure and macroeconomic events impacting liquidity and credit channels.

Table 5 reports the results of conditioning community bank failure on income statement information. Model I shows that all income statement covariates are significant at the one percent level. The negative coefficients on interest income (Intinc), non-interest income (Nonintinc), and net income (Netinc) indicate that a decrease in any source of income increases the risk of failure. The positive coefficients on interest expense (Intexp) and loan and lease loss provisions (LLLP) indicate that an increase in interest expenses and provisions set aside for bad debt subsequently increase bank failure rates. These findings make intuitive sense and are all generally aligned with prior evidence on bank failure research. Similar to conditioning on balance sheet information in the level, we find that the covariates, while statistically significant, tend to be economically small. Model II again controls for macroeconomic conditions but offers no change to the insights gained from model I as the TED spread is insignificant.

Table 5. Cox Survival Model Conditioned on Income Statement and Macroeconomic Covariates.

	Model I Income Statement		Model II Income Statement & Macro	
Variables	Coef.	Hazard Ratio	Coef.	Hazard Ratio
Intinc	-0.000145***	0.999855	-0.000145***	0.999855
Intexp	0.000162***	1.000162	0.000162***	1.000162
Nonintinc	-0.000046***	0.999954	-0.000046***	0.999954
Netinc	-0.000044***	0.999956	-0.000044***	0.999956
LLLP	0.000022***	1.000022	0.000022***	1.000022
Ted_Spread			-1.6341	0.195136
Likelihood Ratio	603.98***		603.99***	
AIC	7,026.10		7,028.09	
BIC	7,060.12		7,068.93	
Log Likelihood	-3,508.04		-3,508.05	
Banks	6,669		6,669	
Failures	452		452	
Obs. (bank-year)	130,495		130,495	

Note. This table presents the Cox regression models based on income statement and macroeconomic information. For each full set of M bank-specific and macroeconomic variables we compare the M regressors and M-1 regressor models and retain the appropriate model based on the following: (1) the significance of the covariates based on the P-values, (2) the likelihood ratio which tests whether β_x=0, (3) the Akaike Information Criteria (AIC), (4) the degrees-of-freedom-adjusted Bayesian Information Criterion (BIC), and (5) the log likelihood ratio best-fit criterion. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Balance sheet and income statement information as conditioning variables provide some useful insights into the uniqueness of community banks, but to examine if there is any kind of differential impact by the covariates on community bank failure we need to analyze financial ratios because of the depth and richness these measure inherently provide. Tables 6 through 9 report the results from conditioning failure on the formerly described financial ratios.

Table 6. Cox Survival Model Conditioned on Capital Adequacy Financial Ratio and Macroeconomic Covariates.

	Model I Capital Adequacy		Model II Capital Adequacy & Macro	
Variables	Coef.	Hazard Ratio	Coef.	Hazard Ratio
Eq_Asset	-23.152800***	8.81E-11	-26.534700***	2.99E-12
Eq_Loanlease	0.000343	1.000343	0.000394	1.000394
Eq_RWA	-17.626100***	2.21E-08	-15.752100***	1.44E-07
Ted_Spread			88.239400***	2.10E+38
Likelihood Ratio	2,704.43***		2,719.88***	
AIC	4,918.66		4,905.22	
BIC	4,939.06		4,932.42	
Log Likelihood	-2,456.33		-2,448.61	
Banks	6,640		6,640	
Failures	452		452	
Obs. (bank-year)	129,904		129,904	

Note. This table presents the Cox regression models based on capital adequacy financial ratio and macroeconomic information. For each full set of M bank-specific and macroeconomic variables we compare the M regressors and M-1 regressor models and retain the appropriate model based on the following: (1) the significance of the covariates based on the P-values, (2) the likelihood ratio which tests whether $\beta_x=0$, (3) the Akaike Information Criteria (AIC), (4) the degrees-of-freedom-adjusted Bayesian Information Criterion (BIC), and (5) the log likelihood ratio best-fit criterion. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 reports the results of conditioning community bank failure on capital adequacy financial ratios. Model I shows that total equity to total assets (Eq_Asset) and total equity to risk-weighted adjusted assets (Eq_RWA) are negative and significant at the one percent level. That is, community banks that have less equity relative to total assets and/or risk-weighted adjusted assets have less protection against unforeseen loan losses and declines in asset values, and are consequently more prone to failure. The magnitude of the coefficients suggests a larger more meaningful economic interpretation from the dataset. However, these findings show no evidence of a differential impact as the sign and magnitude of the covariates align with the results and expectations of prior work regarding US commercial banks in general (see Cole and Wu, 2009; Wheelock and Wilson, 2000; Alali and Romero, 2013). Model II incorporates the macroeconomic control into the specification. The results show no material change in the interpretation of the bank-specific covariates, despite the statistical and economic significance of the TED spreads integration into the model.

Table 7. Cox Survival Model Conditioned on Asset Quality and Liquidity Financial Ratio and Macroeconomic Covariates.

	Model I Asset Quality and Liquidity		Model II Asset Quality and Liquidity & Macro	
Variables	Coef.	Hazard Ratio	Coef.	Hazard Ratio
Loanci_Asset	4.1282***	62.0637	3.2995**	22.9032
Loancon_Asset	-14.7827***	3.80E-07	-15.7227***	1.48E-07
Loanre_Asset	6.2954***	542.0572	5.4737***	238.3401
Chargeoff_Asset	3.7364	63.8391	5.9956	543.2451
LLLP_Asset	-9.6886**	0.000620	-11.3039***	0.000012
Chargeoff_Loanlease	8.6176***	10,899.98	7.7427***	8,0503.30
Loanlease_Dep	4.3949***	123.3961	5.0555***	204.4122
Riskcapt1_RWA	-28.6941***	7.02E-14	-28.4756***	7.35E-14
Ted_Spread			47.2078**	1.60E+24
Likelihood Ratio	2,939.50***		2,944.80***	
AIC	4,693.75		4,690.44	
BIC	4,748.19		4,746.57	
Log Likelihood	-2,338.87		-2,336.22	
Banks	6,641		6,641	
Failures	452		452	
Obs. (bank-year)	129,927		129,927	

Note. This table presents the Cox regression models based on asset quality and liquidity financial ratio and macroeconomic information. For each full set of M bank-specific and macroeconomic variables we compare the M regressors and M-1 regressor models and retain the appropriate model based on the following: (1) the significance of the covariates based on the P-values, (2) the likelihood ratio which tests whether β_x=0, (3) the Akaike Information Criteria (AIC), (4) the degrees-of-freedom-adjusted Bayesian Information Criterion (BIC), and (5) the log likelihood ratio best-fit criterion. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7 reports the results of conditioning community bank failure on asset quality and liquidity financial ratios. Given the channels in which a differential impact for community banking will likely occur due to the differences in lending practices and risk profiles the covariates of particular interest are the loan-to-asset ratios. We include three specific loan-to-asset ratios: commercial and industrial loans to total assets (Loanci_Asset), consumer loans to total assets (Loancon_Asset), and real estate loans to total assets (Loanre_Asset). The remaining covariates in both models are those that prior research has deemed important in bank failure research.

Model I shows that the majority of covariates are highly significant as predictors of community bank failure. Moreover, most take the expected sign consistent with the breadth of prior banking literature. However, consistent with our hypothesis of a differential impact, the consumer loans to total assets covariate takes a negative sign that is both economically and statistically significant at the one percent level. The positive coefficient on the other two loan-to-asset covariates is indicative of the well-documented relationship that banks which are fully lent relative to assets have higher funding risks, and to a lesser extent liquidity risk.[23] This unique finding in the community banking dataset accentuates the importance of the unique knowledge of local market conditions and borrower characteristics by these smaller institutions. That is, an increase in lending in this key market segment relative to assets is essential to community bank survival, seemingly because of their distinctive comparative advantage, or niche, in loans to individuals relative to non-community banks. Model II once again controls for macroeconomic conditions and yields similar results and conclusions as model I.

Table 8 reports the results of conditioning community bank failure on earnings financial ratios. We are most interested in the estimation parameters of the income-based measures of income before extraordinary items to total assets (Incext_Asset) and net operating income to total assets (Netopinc_Asset), as well as the compensation metric (Wage_Asset). We postulate that a differential impact will likely occur through these metrics due to the differences in risk profiles relative to non-community banks and the ability (or lack thereof) of the smaller institutions to securitize and sell loans through special purpose facilities.

Model I shows that all of the covariates are significant at the one percent level as predictors of community bank failure. Each covariate coefficient also takes the expected sign consistent with prior banking research, with the exception of our compensation metric, or more precisely salary and wage expenses to total assets. This latter result is in alignment with our differential impact hypothesis. Banking research typically acknowledges that increases in compensation decrease bank survival as disproportionate compensation is highly inefficient and has a negative impact on overall profitability.[24] Though we do not explicitly include management ratios due to data availability we argue that the Wage_Asset covariate indirectly proxies for management information under the CAMELS categorization. We reason that the strong relational nature of community banking relies on "better" more efficient managers to remain profitable, or more aptly survive. Accordingly, these managers require higher compensation for their efforts. The Wage_Asset covariate is also related to banks' heavy reliance on retaining quality employees with superior relationship building skills and strong ties to the community. In order for the small banks to retain such employees they must pay sufficient wages and benefits to avoid

[23] See Federal Financial Institution Examination Council Uniform Banking Performance Report (UBPR).
[24] Alali and Romero (2013) document a positive but insignificant coefficient for their salary and wages/total assets earnings ratio.

high employee turnover. The reflection of this niche area manifests itself through a very economically large negative coefficient on the proxying covariate (-267.81).

Overall, the result underlies the importance of quality management and employees in the community banking industry.[25] The addition of the macroeconomic control in Model II yields dramatically similar conclusions since the control variable adds little predictive power to the model.

Table 8. Cox Survival Model Conditioned on Earnings Financial Ratio and Macroeconomic Covariates.

	Model I Earnings		Model II Earnings & Macro	
Variables	Coef.	Hazard Ratio	Coef.	Hazard Ratio
Incext_Asset	-4.8288***	0.007997	-4.8316***	0.007974
Netopinc_Asset	-10.5121***	0.000027	-10.4892***	0.000028
Wage_Asset	-267.8146***	4.90E-117	-267.8107***	4.90E-117
ROE	-0.0422***	0.958592	-0.0424***	0.958437
Ted_Spread			14.1004	1,329,615
Likelihood Ratio	1,332.97***		1,333.22***	
AIC	6,295.27		6,297.02	
BIC	6,322.49		6,331.04	
Log Likelihood	-3,143.64		-3,143.51	
Banks	6,669		6,669	
Failures	452		452	
Obs. (bank-year)	130,517		130,517	

Note. This table presents the Cox regression models based on earnings financial ratio and macroeconomic information. For each full set of M bank-specific and macroeconomic variables we compare the M regressors and M-1 regressor models and retain the appropriate model based on the following: (1) the significance of the covariates based on the P-values, (2) the likelihood ratio which tests whether β_x=0, (3) the Akaike Information Criteria (AIC), (4) the degrees-of-freedom-adjusted Bayesian Information Criterion (BIC), and (5) the log likelihood ratio best-fit criterion. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9 reports the results of the aggregate financial ratio model. The collective results in Model I are similar to the specifications from Tables 6 through 8. The differential results for consumer loans and compensation remain significant though the estimated magnitude of their impact is slightly diminished in both cases. The only notable change from the prior tables is that the net operating income to assets (Netopinc_Asset) covariate is rendered statistically insignificant in the more robust model. Model II incorporates the macroeconomic control and yields similar insights to model I. While the TED spread is statistically and economically impactful, its

[25] Unfortunately, we cannot disentangle the impact of the manager and employees due to data limitations.

incorporation renders the earnings ratio income before extraordinary items to total assets (Incext_Asset) insignificant.

Table 9. Cox Survival Model Conditioned on Aggregate Financial Ratio and Macroeconomic Covariates.

	Model I Aggregate		Model II Aggregate & Macro	
Variables	Coef.	Hazard Ratio	Coef.	Hazard Ratio
Eq_Asset	-21.3457***	1.94E-09	-23.5302***	6.04E-10
Loanci_Asset	4.4477***	94.4175	4.4448***	85.5493
Loancon_Asset	-9.0839***	0.000298	-8.7265***	0.000162
Loanre_Asset	4.7172***	92.4997	5.1212***	167.5390
Chargeoff_Asset	5.7932	1,826.46	7.7143	2,240.13
LLLP_Asset	-21.5818***	1.71E-09	-19.3486***	3.95E-09
Chargeoff_Loanlease	3.1849*	32.3611	3.1453*	31.9530
Loanlease_Dep	2.8442***	58.1826	3.2757***	85.7893
Riskcapt1_RWA	-15.0648***	1.08E-8	-14.3231***	1.83E-7
Incext_Asset	-5.7086*	0.003317	-3.6966	0.018330
Netopinc_Asset	-0.535631	0.947846	-0.22792	0.997212
Wage_Asset	-180.9045***	2.72E-78	-178.6657***	2.55E-78
ROE	-0.025501***	0.097566	-0.026181***	0.076654
Ted_Spread			82.3369***	2.28E+38
Likelihood Ratio	3,347.59***		3,367.25***	
AIC	4,291.65		4,275.96	
BIC	4,392.87		4,364.37	
Log Likelihood	-2,134.83			
Banks	6,641		6,641	
Failures	452		452	
Obs. (bank-year)	129,9927		129,9927	

Note. This table presents the Cox regression models based on aggregate financial ratio and macroeconomic information. For each full set of M bank-specific and macroeconomic variables we compare the M regressors and M-1 regressor models and retain the appropriate model based on the following: (1) the significance of the covariates based on the P-values, (2) the likelihood ratio which tests whether β_x=0, (3) the Akaike Information Criteria (AIC), (4) the degrees-of-freedom-adjusted Bayesian Information Criterion (BIC), and (5) the log likelihood ratio best-fit criterion. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5. Concluding remarks

The last 40 years have seen the community banking sector markedly shrink. Yet, in spite of this decline community banks continue to play a vital role in key lending segments of the US economy. Due in part to their distinctive risk profiles from larger banks, homogenous earnings streams, and lack of involvement in the capital markets we hypothesize that bank-specific covariates relating to asset quality and earnings may have a differential impact on community bank failure risk as compared to non-community banks, which have well-documented salient features. This study contributes to the banking literature by providing a more detailed understanding of the uniqueness of the community banking industry. Such information could be used, for instance, in conjunction with current early warning bank failure models to help assist institutions in recognizing potential deficiencies.

We examine our differential hypothesis using survival analysis and a comprehensive set of bank accounting information. In contrast with prior literature, our empirical results analyzing balance sheet information indicate that smaller community banks are less likely to fail than their larger community bank counterparts. More importantly, in support of the differential impact hypothesis, financial ratio information encompassing capital adequacy, asset quality and liquidity, and earnings, shows that community banks that reduce their proportion of consumer lending as a percentage of total assets (Loancon_Asset) are more likely to fail. This result comes in stark contrast to current bank literature which shows that banks that are fully lent relative to assets have increased failure risk. Additionally, the salary and wage expenses to total assets ratio (Wage_Asset), which we argue indirectly proxies for managerial and employee effectiveness and efficiency, is statistically and economically significant. However, the covariate is of the opposite sign typically documented in the banking literature. Given the strong personal nature of community banking, higher levels of compensation are not simply excessive rents that contribute to increased failure, but a necessary cost of the industry to obtain and retain quality talent that is critical to survival.

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