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Determinants of Failures of Credit Unions and Commercial Banks: Similarities and Differences

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Abstract

The surge of failures of credit unions and commercial banks during the recent financial crisis revived interest in their causes. Compared with bank failures, credit union failures have rarely been analyzed systematically. The evolving size and devolving regulation of credit unions relative to smaller banks spurred us to analyze and compare the failures of credit unions to those of banks.

This is the first, large-scale, long-term analysis of credit union failures that applies the methods long standard in studies of bank failures. We constructed a new database based on the financial statements and failures of credit unions for 1979-2016. We used the new database to estimate failure equations for credit unions and for banks. Our logits distinguished the effects of credit unions' and banks' own financial conditions from the effects of their local economic conditions.

Credit unions failed for some of the same reasons as banks:. Both credit unions and banks failed more when they had more commercial mortgages, fewer assets, more delinquent loans, more noninterest expenses, less capital, and lower ROAs.

Credit unions also failed for different reasons. Having more residential mortgages led to more failures of credit unions, but not of banks. Conversely, having more business loans and more local unemployment signaled more failures of banks, but not of credit unions.

We used size-specific estimates of one-year-ahead failure probabilities to assess how much their risks changed due to own and to economic conditions. Following the turbulent early 1990s, credit union risks fell much more than risks at banks of the same size. In the years around the crisis, due to the relative deterioration of banks' conditions, larger shares of banks than credit unions had high risks of failure.

Determinants of Failures of Credit Unions and Commercial Banks: Similarities and Differences

Failures of credit unions have been relatively rare. Even rarer have been systematic analyses of the causes of failures of credit unions. During the quiescent period of the "Great Moderation" of the macroeconomy that ended with the recent financial crisis and recession, failure rates of credit union and of banks sank to historic lows. During and after the crisis, the numbers of failures of credit unions and even more of banks rebounded. In the years 2008-2016, 168 credit unions and over 520 banks failed.

The evolving size and devolving regulation of credit unions relative to smaller banks spurred us to analyze and compare the failures of credit unions to those of banks. The analysis may be useful to those who may be affected by actual or prospective failures: uninsured creditors (such as some depositors and debt holders), firms that rate the creditworthiness of financial institutions, deposit insurers (the National Credit Union Administration (NCUA) and the Federal Deposit Insurance Corporation (FDIC)), and taxpayers. The volume of studies of failures of banks tends to rise and fall soon after the numbers of failures rise and fall. Our analysis is an example. In addition to systematically analyzing bank failures through 2016, we try to identify the similarities and differences in failures of credit unions and of banks. These patterns may provide insight into the risks of each category of depository that would not have emerged so clearly without having analyzed both categories.

Ours is the first, large-scale, long-term, study of failures of credit unions that is based on the statistical methods that have long been the standard for studies of failures of banks.[1] In

1. For expository convenience, here we use the term "banks" to mean commercial banks and thrifts. Here we update the data and methodology from Wilcox (2007).

addition to bearing directly on the determinants of failures, our results may also have implications for the effects of credit unions' mutual, as opposed to banks' stock, ownership of depositories on efficiency, pricing, portfolios, and activities.

We use a newly-constructed database that records the financial statements and failures of credit unions since 1979. We then present the first, large-scale, long-term analysis of credit union failures. While comparing the overall failure rates of credit unions and commercial banks turns out to be complex, credit union failure rates have typically been lower than those of commercial banks of similar sizes.

We estimated and compared logits that accounted for failures of credit unions and of commercial banks with their local economic and financial conditions. Factors that have long been associated with failures of banks are also often associated with failures of credit unions. Both credit unions and commercial banks were more likely to fail when they had more commercial mortgages (i.e., business loans backed by real estate), smaller asset size, more delinquent loans, more noninterest expenses, less capital, and lower ROAs.

However, we also found some substantial differences between credit unions and banks in the estimated models of their failures. Compared with those for banks, the factors that affected the failures of credit unions sometimes differed in size or in statistical significance. Even within credit unions or banks, the size and significance of the factors also sometimes differed by institutions' asset sizes and by subperiods. Having more residential mortgages signaled more failures of credit unions, but not of banks. Conversely, having more commercial and industrial (C&I) loans and higher local unemployment rates signaled more failures of banks, but not of credit unions.[2] These findings may suggest how loan portfolios could be shifted to reduce failure

2. C&I loans are business loans that are not backed by real estate.

risk. Though other considerations would also be relevant, the estimates suggest that replacing some residential mortgages with C&I loans could reduce failures of credit unions. Similarly, replacing some holdings of C&I loans with residential mortgages might reduce failures of commercial banks.

Our results on what characteristics have historically placed depositories more or less at risk of failure serve as a natural springboard from which to design various risk-based policies to provide incentives for depositories to operate in manners that are more "safe and sound." For instance, results from statistical analyses like ours might be used to inform both risk-based capital requirements for credit unions and, potentially, risk-based premiums for their deposit insurance. Of course, as our results themselves show, such risk-based policies may need to be updated periodically taking into account long-term changes in what factors are more or less reliable predictors of failure.

Failures of both credit unions and of banks rose from the earlier, quiescent subperiod (1994-2007) to the financial crisis subperiod (2008-2013). The increase in the (average, annual) failure rate of credit unions was much smaller (from 0.18 to 0.27%) than the increase for commercial banks (from 0.05 to 1.02%). We looked to see whether the relative increase in the failure rate of banks could be accounted for by the relative deterioration of banks, as indicated by changes in the measured factors that were included in the failure equations. To do so, we used size-specific estimates of failure-prediction equations for credit unions and for banks to calculate for each depository its one-year-ahead probability of failure (EPF). We then tabulated the numbers of credit unions and of banks that had EPFs greater than a threshold value of 0.1% (10 basis points). We regarded 10 basis points as a Basel-like threshold above which a bank could be considered "high risk." We calculated EPFs for four years 1990, 2000, 2010, and 2017. Because we used the same estimated failure equation for each of the four years, we attribute these calculated changes in EPFs solely to changes in each depository's conditions, as measured by the factors or explanatory variables in the failure-prediction equations.

Credit unions had far larger declines on average in calculated EPFs from the first, troubled subperiod (1987-1993) to the subsequent, quiescent subperiod (1994-2007) than banks did. From the first to the subsequent subperiod, the share of smallish credit unions (i.e., those with assets between $10 M and $100 M) that were high risk, for example, fell from 36% to 7%, while the high-risk share of smallish banks fell from 44% to 20%. More interestingly, from the quiescent subperiod to the crisis subperiod, we tabulated fewer credit unions than banks that became high risk. The share of medium (sized) credit unions (i.e., those with assets between $100 M and $1 B) that were high risk rose from 7% to 8%, while the high-risk share of medium banks rose from 25% to 47%. These calculations suggest that the relative rise in the failure rate of banks might be importantly attributed to the relatively more severe deterioration of banks' conditions.

The remainder of this paper proceeds as follows. Section 1 reviews the literature on failures of commercial banks, mutual and stock thrifts, and credit unions. Section 2 compares failure rates of credit unions to those of banks. Section 3 discusses the statistical methods that we used to predict failures of credit unions and of banks. Section 4 presents estimated logit models for failures of credit unions and failures of banks, by asset sizes and for subperiods of our entire 1980-2016 sample. Section 5 shows summary statistics for the variables that were included in logits. It also shows distributions of estimated probabilities of failure of credit unions and of banks, by asset sizes and for subperiods. Section 6 briefly concludes.

1. Literature review

The flow of studies that focus on failures of depositories ebbs and flows with the volume of failures and losses they impose. In the decade before the recent financial crisis, both failures and studies of failures were rare. On the heels of the literally thousands of failures of depositories, mostly thrifts, from the early 1980s through the middle of the 1990s, much attention was devoted to uncovering the determinants of future failures of depositories. Banks were the depositories that were first to be analyzed econometrically. Failures of banks also garnered by far the most academic interest. Banks' supervisory agencies have long used econometric models akin to those found in academic studies. Failures, and attention to failures, of thrifts both exploded during the 1980s and early 1990s. Many studies of thrifts in general, and of failures of thrifts in particular, considered whether mutual (as opposed to stock) ownership affected whether thrifts failed. Because credit unions are mutually owned and commercial banks are shareholder, or stock, owner, studies of ownership effects may highlight possible differences between credit unions and banks that are germane to their likelihoods of failure. Compared with banks and thrifts, failures of credit union failures have been studied only sporadically and rarely econometrically. We have not found direct comparisons by other authors of the systematic aspects of failures of banks with those of credit unions.

1.1. Empirical methods and findings: commercial banks

Seminal studies by Beaver (1966) and Altman (1968) produced econometric models using financial ratios that could predict the bankruptcy (i.e., failure) of business firms. Many similar papers followed focusing on depository institutions. Among the earliest studies of failures in depository institutions using econometric models are Meyer and Pifer (1970) focusing on commercial banks, Altman (1977) focusing on thrifts, and Kharadia and Collins (1981) focusing on credit unions.

The increased availability of computer power has made possible testing an increasing variety of statistical techniques with large databases of individual depository institutions. The techniques employed range among others from ordinary least squares (OLS) (Meyer and Pifer 1970) to discriminant analysis (Sinkey 1975), probit (Hanweck 1977), binomial logit (Martin 1977), factor analysis (West 1985), difference of means tests (Rudolph and Hamdan 1988), proportional hazards (Whalen 1991), trait recognition (Kolari et al. 2001), Markov models (Glennon and Golan 2003), and multinomial logit (Oshinsky and Olin 2005). Demirguc-Kunt (1989), Altman and Saunders (1998) and King et al. (2006) provide reviews of the literature on attempts by econometric models to predict failures of depository institutions.

While every statistical technique is likely to have some advantages and shortcomings, the logistical specification (logit) has long been the standard in failure studies (King et al. 2006). Martin (1977), for instance, argues that logit is preferable to discriminant analysis since logit does not require the sample sizes of the two categories to be compared to be matched, obviating restricting one's samples. Logit's staying power is perhaps best attested to by proponents of other techniques who routinely compare their techniques to logit.

Aside from pioneering the use of logit, Martin (1977) set the standard for studies of failure in depository institutions in several ways. He experimented with a variety of financial ratios, settling on measures of capital adequacy, asset quality, earnings, and liquidity as the most significant determinants of failure. The main bank rating system used by U.S. supervisory agencies, the Uniform Financial Rating System or CAMELS, reflects the importance of largely the same set of variables in predicting failure. Adopted in 1979, the rating system included capital adequacy (C), asset quality (A), management competence (M), earnings performance (E), and liquidity risk (L). Sensitivity to market risk (S) was added in 1997. Most failure studies have routinely used similar lists of variables, largely drawn from Call Report data, and largely continue to find them to be significant (King et al. 2006).

Supervisory banking agencies have long validated the emphasis of the academic literature on financial ratios and their formal statistical analysis in the development of Early Warning Systems (EWS) that use data updated quarterly to predict the failure of depository institutions. Supervisors use these off-site systems to supplement the information they receive in onsite examinations, seeking to prevent some failures or to reduce the costs of those failures (Kolari et al. 2001 and Jordan and Rosengren 2002, 5).

King et al. (2006) review in detail the evolution of off-site surveillance models used by supervisory agencies. The earliest formal step in this direction was the National Bank Surveillance System (NBSS), adopted by the OCC in 1975. Constrained by computational costs, the NBSS simply allowed supervisors to rank banks according to financial ratios to detect outliers within peer groups. In 1977, the Federal Reserve launched the Minimum Bank Surveillance System (MBSS). Weighing seven financial ratios by z-scores, this system was the first surveillance model used by a supervisory agency that used econometric techniques (Korobow, Stuhr, and Martin 1977). After experimenting with a variety of models, the Federal Reserve has since 1993 used logit in its System to Estimate Examination Ratings (SEER) to predict probabilities of failure (King et al. 2006).

Martin (1977) also deviated from earlier studies that focused on small samples of banks over short time spans. His study used all Fed-supervised institutions over a period of 7 years during the 1970s, yielding over 30,000 observations. Several other studies employing econometric models have also investigated failures over long time spans. Harrison and Ragas (1995) and Fuller and Kohers (1994) study thrift failures respectively in 1980-89 and 1983-91. Jordan and Rosengren (2002) investigate commercial bank failures in 1985-2001. Oshinsky and Olin (2004) studied troubled banks in 1990-2002.

As failures have now been studied using econometric models for several decades, a number of studies document the large variation in the experience of failures and insurance losses from commercial banks and the variations in the coefficients and statistical significance of explanatory variables over time, under different macroeconomic, regulatory, or industry conditions. Hanc (1998) studies in detail the evolution of the number of failures in commercial banks during the 1980s and early 1990s and reviews the likely causes. Kaufman (2004) documents the sizable differences in the number of commercial bank failures, losses to the FDIC from those failures, and losses per assets in failing institutions for two extended periods before and after the Federal Deposit Insurance Corporation Improvement Act (FDICIA) (in his study 1980-92 and 1993-2002).

Fuller and Kohers (1994), Harrison and Ragas (1995), and Helwege (1996) compare the estimates from models predicting thrift failures across different time periods. King et al. (2006) compare the characteristics of failing and surviving commercial banks in 1984-94 and 1995-2003. Each of these studies found that the lists of variables likely to be significant in explaining failure have been roughly similar across periods, but that the size of coefficients (and thus their economic significance) could vary greatly across periods. For instance, King et al. (2006) report that during their earlier period failing commercial banks were larger than average, held more commercial mortgages, and did not experience climbing cash levels before failure. During the latter period, each of those warning signs was reversed or was no longer predictive. Using a multinomial logit technique, Oshinsky and Olin (2004) similarly find changes in the patterns of bank problems and failures. They report that in the early 1990s most banks classified as troubled remained troubled 6-24 months later. By the late 1990s, however, most banks classified as troubled would recover within 6-24 months.

Availability (and unavailability) of different types of data and of populations sufficiently large to permit meaningful statistical analysis have determined the shape of many avenues in the research of failures. Since commercial bank failures grew increasingly rarer during the mid-2000s, the paucity of data made it more difficult to update models meaningfully to reflect the characteristics that were likely to be associated with failures in the future. Thus, several authors noted that whereas supervisory off-site models were used to produce new estimates of likely failures based on new data quarterly, the variables used and their coefficients were long based on the failure experience of 1985-92 and would unavoidably be less well attuned to the factors contributing to failures during the most recent economic crisis (Jordan and Rosengren 2002 and King et al. 2006).

The characteristics and mechanics (e.g., too big to fail policies) of failures for institutions of different sizes have long been suspected to be different. For instance, Kaufman (2004) contrasts failures, losses, and loss to asset ratios in commercial banks of different asset sizes. King et al. (2006) find that failing banks on average were larger than surviving ones in 1984-94 but were smaller in 1995-2003. However, the small number of large banks failing has limited the ability to study large bank failures separately from smaller institutions. Demirguc-Kunt (1989) and Kolari et al. (2001) are among the few studies to model the characteristics of failing commercial banks segregated by assets. Even in those studies, the paucity of data forces the time span covered to be short (e.g., 1989-92 in Kolari et al. 2001) limiting its predictive capacity for other periods.

Many studies of failures (e.g., Glennon and Golan 2003) have used as explanatory variables both financial data for individual institutions and different measures of state macroeconomic performance. However, much the literature on the use of state macro variables in failure models is mixed. For instance, Nuxoll (2003) reports that models that include macroeconomic variables do not perform significantly better than models that do not include them. However, Jordan and Rosengren (2002) find that macroeconomic forecasts provide little additional information over bank-specific financial data in predicting failures during prosperous times, but are relevant during troubled periods.

1.2. Rationales and incentives: Mutual and stock thrifts

Interest in thrift failures rose with thrift failure rates during the 1980s and early 1990s. Since the end of the thrift crisis in the mid-1990s, thrift failures and studies about them have both been rare. Many studies of thrifts consider the potential impact of organizational form (mutual vs. stock) on efficiency, asset mix, and failures. These studies may serve to highlight some of the possible differences between commercial banks and credit unions. Agency theories posit that different agents (customers, managers, stockholders, debtholders, etc.) within firms may have conflicting interests. Different forms of organization (e.g., mutual vs. stock) may be better or worse attuned to solving some of these conflicts. Mutuals are often thought as better than stock companies at solving customer-owner conflicts (essentially by merging the two), but worse at solving manager-owner conflicts. Having members as their sole constituency, mutuals might provide products and services to their members at a lower cost. CUNA annual membership benefit reports routinely show that on average customers pay lower loan rates and receive higher deposit rates on most individual products at credit unions than at commercial banks.

In contrast, Rasmusen (1988), among others, argues that mutuals typically have weak governance structures. Absent transparent means to measure how much value members receive from their mutual institution and absent effective means for individual concerned members to remove management, managers are largely self-controlled. Lacking a clear means to link managerial performance and compensation, better managers will be underpaid and worse managers will be overpaid. Thus, rather than maximizing value for members, managers might grant themselves extensive non-monetary perks or reduce the risks to their future position by incurring less risk (and thus returns) than their members might prefer. Similarly Harris and Raviv (1991) describe a possible asset substitution conflict between stockholders and debtholders in stock firms, where stockholders would prefer banks to engage in riskier activities (such as commercial mortgages) more than debtholders.

Whereas the broad implications of theories on the impacts of organizational form are largely settled, evidence on the performance and efficiency of mutual vs. stock thrifts is mixed. Using different sample periods, Vergrubbe and Jahera (1981), Akella and Greenbaum (1988), and Sfiridis and Daniels (2004) find mutual thrifts to be less efficient than stock thrifts. In contrast, Cebenoyan et al. (1993b) did not find efficiency to be significantly related to organizational form. Searching for an explanation to the conflicting evidence, Hermalin and Wallace (1994) investigate the impact of asset mix on efficiency. They report that ignoring asset mix, stock thrifts appear on average less efficient than mutual thrifts. Holding constant for asset mix, they found that stock thrifts engaging in similar activities operated more efficiently than mutual thrifts.

From these findings, Hermalin and Wallace conclude that stock thrifts were better at resolving agency conflicts between owners and managers (i.e., they could operate at a lower cost for a given set of business lines), but worse at resolving the asset-substitution conflict between shareholders and debtholders (i.e., they held riskier assets). Similarly Esty (1997) found stock thrifts to exhibit greater profit variability and thrifts that converted from the mutual to the stock form to increase their investments in risky assets and profit variability. Gropper and Hudson (2003) found that, as standard theory might predict, increased competition during the 1980s removed most evidence of a difference in efficiency between mutual and stock thrifts.

Evidence on failures and failure costs in mutual vs. stock thrifts is also mixed. Some results are straightforward and consistent across studies: Cebenoyan et al. (1993a) and Hermalin and Wallace (1994) find measures of inefficiency to be significant predictors of failures in both mutual and stock thrifts. Other results are more complex or disputed. Benston (1985) and Harrison and Ragas (1995) include a mutual vs. stock variable in their failure models and do not find organizational form to be a significant predictor of failure. In contrast, Chou and Cebula (1996) find that states with a higher proportion of stock thrifts experienced more thrift failures.

Hermalin and Wallace (1994) also find asset mix pivotal in explaining failures in mutual vs. stock thrifts. Ignoring asset mix, they found stock thrifts to fail more often than mutual thrifts. Holding constant for asset mix, stock thrifts engaging in similar activities were less likely to fail than mutual thrifts. Whereas these findings might imply that the stock form might otherwise be less prone to failure, they also imply that the activities that stock thrifts tend to engage in may make them more prone to failure. Similarly, Barth et al. (1990) find organizational form not to be significant in predicting failure costs, but speculate that the effects typically associated with the stock form would likely have been already captured elsewhere in their model.

The links between organizational form, efficiency, and failure might also have been obscured by the difference between (1) sudden regulatory failure and (2) slow growth and shrinking market share. Rasmusen (1988) argues that, absent deposit insurance, mutual and stock depositories could readily coexist in the marketplace. Stock depositories would specialize in providing some savers (depositors), managers, and investors (stockholders) with high-risk, high-return saving, compensation, and investment options backed by higher-risk loans. In contrast, mutual depositories would specialize in providing other savers and managers with low-risk, low-return options backed by lower-risk loans. Thus Rasmusen finds that from the nineteenth century through the Great Depression, mutual depositories failed less often than stock depositories.

Rasmusen's theory implies that unless other countervailing government assistance (such as tax exemptions) were provided to mutuals, providing federal deposit insurance to stock depositories would make deposits in mutual and stock depositories similarly risky and remove a key incentive for depositors to use mutuals. This could explain why as mutual thrifts progressively lost their income tax exemptions between 1952 and 1996, their number of institutions and their (assets) market share plummeted from 4,148 and 26.4% in 1965 to 979 and 2.9% in 1996, and to 379 and 0.8% in 2016.[3] Having lost a key advantage and faced with greater difficulty in controlling costs, mutual thrifts would have dwindled not as much through outright failures, but through lower growth (and conversions into the stock form). During the same period, credit unions (i.e., also a type of mutual depository, but one that did not lose its tax exemption) have continued to thrive, with market shares growing from 1.9% in 1965 to 5.7% in 1996 and 7.2% in 2016.

3. The number of mutual institutions reported includes those insured by the Federal Savings and Loan Insurance Corporation (FSLIC 1934-1989) and the FDIC. Market share is expressed as a percentage of assets in the total of commercial banks, mutual and stock thrifts, and credit unions.

1.3. Studies of failures of credit unions

The historical evolution of failures at credit unions has been described in several studies. Croteau (1952) and Kelly and Karofsky (1999) present the evolution of the number of failures of federal credit unions (i.e., excluding state-chartered credit unions) for respectively 1935-51 and 1935-1970. Examining data for individual credit union failures without using econometric models, Gordon et al. (1987), Gordon (1991), and Shafroth (1997) identify a number of variables as likely to play a role in credit union failures and losses (respectively for 1981-85, 1986-91, and 1995-96). Some of these variables are akin to those found in studies of commercial bank and thrift failures: riskier assets (residential mortgages and business loans) and high noninterest expenses. These authors also suggest some additional issues that are more idiosyncratic to credit unions, and particularly to the smallest of credit unions: small size, youth (i.e., a recent chartering), sponsor failures, poor record keeping, weak lending and collection practices, and refinancing delinquent loans.

Wilcox (2005) presents the most comprehensive recent study of the evolution of failures and insurance losses for federally-insured credit unions. Wilcox contrasts the evolution of failures and insurance losses at credit unions and commercial banks and the characteristics of failing and surviving credit unions, for institutions of different sizes and for different time subperiods within 1971-2004 (i.e., since the inception of federal insurance for deposits[4] in credit unions). Credit union failures and insurance losses generally compare favorably with those of commercial banks (see Figure 1, 2, and 3 below). Among credit unions, smaller asset size, lower

4. In credit unions, the analog to deposits in banks are often called shares or savings. For simplicity, throughout this, we refer to credit union savings and shares as deposits.

capital, higher loan to asset ratios, higher noninterest expenses, and more delinquent loans were associated with higher failure rates.

However, studies applying econometric models to credit union failures have been relatively rare. For instance, Kharadia and Collins (1981) used OLS to model failures of federal credit unions in 1960-71. Kane and Hendeshott (1996) used logit to model failures of federally-insured credit unions in 1987-1990. Wilcox (2007a) presented an earlier version of this study for 1981-2005, thus not including data for the most recent period of high failure rates and/or insurance losses among depository institutions.

2. Data for Failures and Insurance Losses

We obtained aggregate and individual data for failures of natural person federally-insured credit unions and commercial banks for 1971-2016 from the NCUA and the FDIC (2017).[5] We obtained call report data for individual credit unions and commercial banks for 1979-2016 from the NCUA (2017a), the Federal Reserve Bank of Chicago (FRB Chicago 2017), and the Federal Financial Institution Examination Council (FFIEC 2017). Table 1 presents annual failure rates and the number of failures in credit unions and commercial banks for several time periods and asset size ranges.[6] We include two subperiods (1980-1993 and 2008-2013) during which failure rates were higher and two "quiescent" subperiods (1994-2007 and 2014-2016) during which failure rates were lower.[7] To calculate average failure rates for each subperiod, we first compute

5. Throughout this paper for simplicity, we use the term credit union to refer exclusively to federally-insured credit unions, excluding credit unions that were either uninsured or insured by non-federal entities. Thus, all data, including counts of credit unions and asset totals, refer only to federally-insured credit unions. 1971 is the year of the launch of federal deposit insurance for credit unions. We also focus on natural person credit unions, which serve individuals, instead on corporate credit unions, which serve other credit unions.
6. Since we report failure rates across asset size ranges, in Table 1 we used financial data for individual institutions experiencing failure and could not include data prior to 1979.
7. We further subdivide 1980-1993 into 1980-1986 and 1987-1993 since credit unions and commercial banks reported far more of the variables that we use in most of our models for the latter period (Tables 2-5) than for the earlier period (Table 6).

annual failure rates (i.e., the number of failures during one year relative to the number of institutions on the previous December 31) and then average those annual failure rates across the years included in a subperiod. For each variable in the table, we present values for all credit unions and commercial banks, and for institutions under $10M in assets (i.e., tiny), with between $10M and $100M (i.e., smallish), with between $100M and $1B (i.e., medium), and over with over $1B (i.e., large), with all boundaries between asset sizes adjusted for inflation expressed in 2016 dollars.[8] Table 1 also includes the number of institutions on several dates (i.e., those at the boundaries of the subperiods that we use throughout) to highlight the evolution of the various asset size groups. For instance, large credit unions were rather rare until relatively recently, and tiny banks have long been relatively rare.

8. Wilcox (2005) presents results for credit unions across narrower asset size ranges including under $1M in assets (tiny) and between $1-10M (very small).

Table 1

Failures Rates and Failures of Credit Unions and of Commercial Banks,

by Size and by Subperiod

	Credit Unions					Commercial Banks				
	All (1)	Tiny (2)	Smallish (3)	Medium (4)	Large (5)	All (6)	Tiny (7)	Smallish (8)	Medium (9)	Large (10)
A. Failure rate (%)										
1. 1980-1986	0.86	1.00	0.22	0.07	0	0.42	0.90	0.53	0.24	0.11
2. 1987-1993	0.79	1.00	0.41	0.22	0	1.07	1.30	1.25	0.83	0.86
3. 1994-2007	0.18	0.32	0.05	0.02	0	0.05	0.09	0.05	0.04	0.04
4. 2008-2013	0.27	0.40	0.16	0.30	0.10	1.02	1.45	0.60	1.12	1.96
5. 2014-2016	0.24	0.66	0.07	0.03	0	0.16	0.00	0.32	0.09	0.12
6. 1980-2016	0.44	0.62	0.17	0.11	0.02	0.48	0.68	0.48	0.41	0.53
B. Number of failures										
7. 1980-1986	996	949	43	2	0	422	14	314	90	4
8. 1987-1993	741	616	114	11	0	979	13	636	292	35
9. 1994-2007	264	230	31	3	0	58	1	30	24	3
10. 2008-2013	119	65	31	22	1	418	4	78	267	69
11. 2014-2016	45	38	6	1	0	27	0	16	9	2
12. 1980-2016	2,165	1,898	227	39	1	1,904	32	1,074	682	113
C. Number of institutions										
13. 1979	17,482	14,526	2,664	289	3	14,355	259	8,695	4,927	473
14. 1986	14,693	10,232	3,790	647	17	14,171	169	7,863	5,538	594
15. 1993	12,317	7,089	4,309	880	36	10,960	83	5,734	4,583	560
16. 2007	8,101	3,364	3,388	1,200	148	7,356	81	2,675	4,011	589
17. 2013	6,554	2,138	2,921	1,273	217	5,911	37	1,768	3,553	553
18. 2016	5,785	1,659	2,575	1,279	272	5,163	29	1,371	3,157	606

Note: all boundaries between asset sizes are adjusted for inflation, expressed in 2016 dollars. Tiny institutions have fewer than $10 million (M) in assets, smallish have $10-100M, medium have $100M - $1 billion (B), and large have more than $1B.
Sources: NCUA (2017a), FDIC (2017), FRB Chicago (2017), and FFIEC (2017).

Table 1 shows that failure patterns have differed substantially between credit unions and commercial banks. Failure rates fell substantially from their earlier high levels during a subperiod (1987-1993) associated with the thrift crisis to the following quiescent period (1994-2007) for both credit unions (from 0.79% to 0.18%) and commercial banks (from 1.07% to 0.05%). However, failure rates increased far less during the financial crisis for credit unions (from 0.18% to 0.27%) than for commercial banks (from 0.05% to 1.02%). Averaged over the extended period of 1980-2016, credit unions' failure rates were somewhat lower (0.44%) than commercial banks' (0.48%).

Smaller institutions used to fail consistently more often than larger ones. This pattern was clearest among credit unions, where “tiny,” small, medium, and large institutions had failure rates of 1.00, 0.22, 0.07, and 0.00 during the earliest subperiod and of 0.32, 0.05, 0.02, and 0.00 during the quiescent subperiod of 1994-2007.[9] The pattern was less pronounced among commercial banks, with failure rates of 0.90, 0.53, 0.24, and 0.11 during the earliest subperiod, but of 1.30, 1.25, 0.83, and 0.86 during the second subperiod. However, the link between smaller size and more failures has broken down during the most recent “crisis” subperiod, with credit union asset size groups experiencing failure rates of 0.40, 0.16, 0.30, and 0.10, and commercial bank asset size groups experiencing failure rates of 1.45, 0.60, 1.12, and 1.96.

Comparing institutions of the same sizes, credit unions generally had lower failure rates than commercial banks, i.e., 0.62 vs, 0.68 for tiny institutions, 0.17 vs. 0.48 for smallish institutions, 0.11 vs. 0.41 for medium institutions, and 0.02 vs. 0.53 for large institutions.

Figures 1 through 3 further elaborate on the differences between credit union and commercial bank failures and insurance losses. Figure 1 presents annual failure rates of credit unions and commercial banks during 1971-2016.[10] Annual failure rates have often been higher for credit unions than for commercial banks. Annual credit union failure rates averaged 0.48% (during 1971-2016) and peaked at 1.51% in 1980. Annual commercial bank failure rates averaged 0.39% during the same period and peaked at 1.91% in 2010. Like Table 1, Figure 1 highlights that failure rates can exhibit alternating periods of high and low values that only partially overlap for credit unions and commercial banks.

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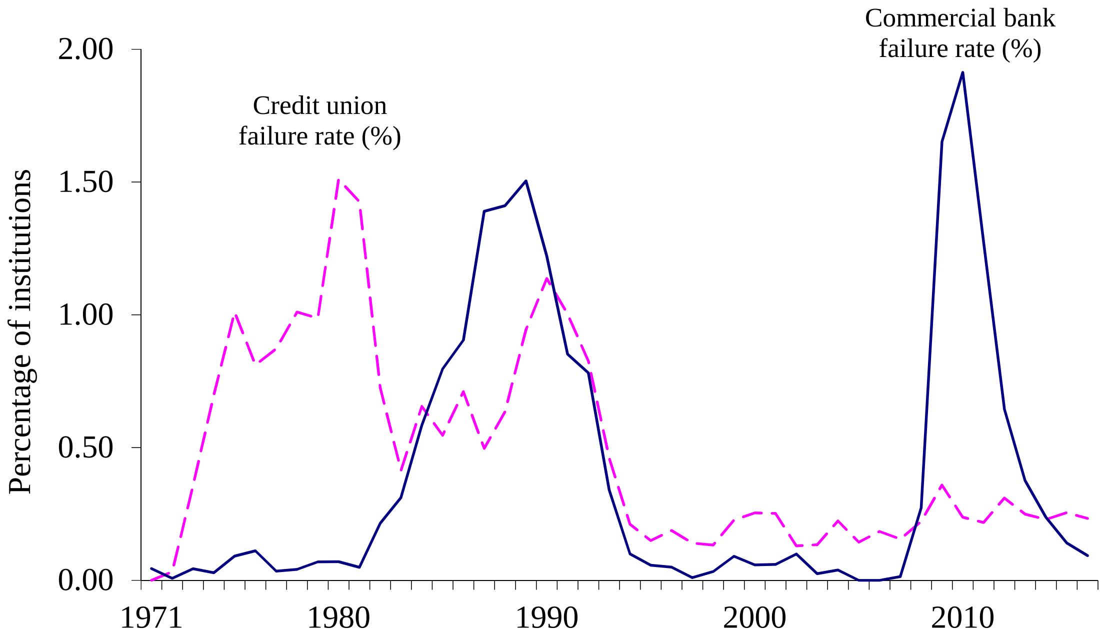
9. For ease of presentation, in the following sentences that include long strings of numbers, we omit the percent signs.

10. Since this figure does not break down failure rates across asset size ranges, we report it since 1971 instead of 1981.

Figure 1

Failure Rates of Credit Unions and of Commercial Banks, 1971-2016



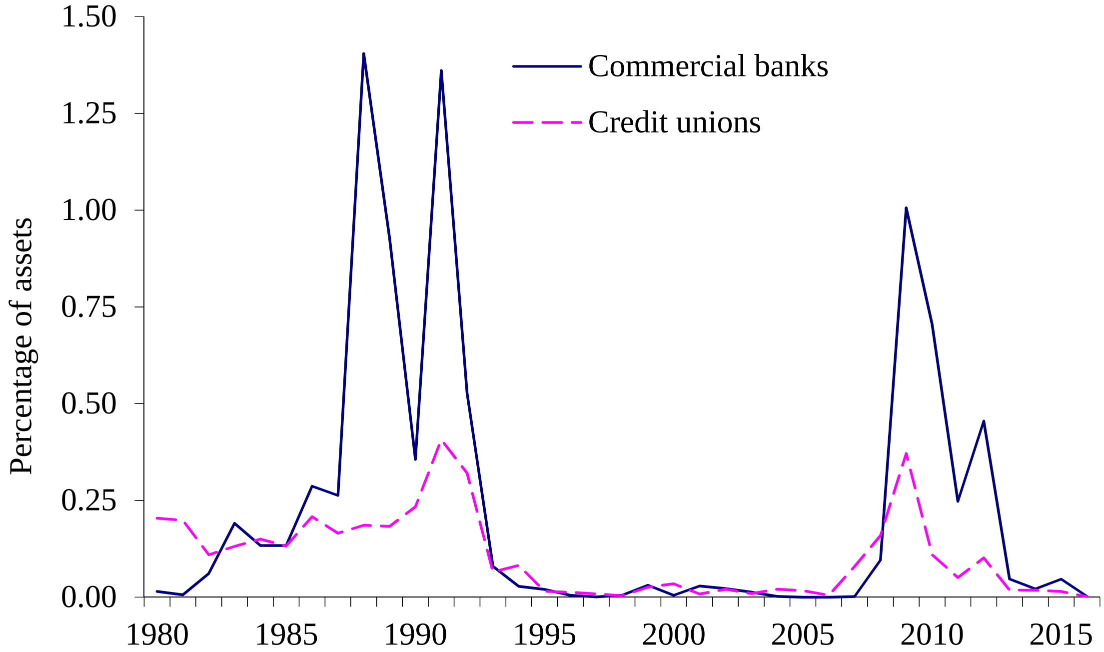
Sources: Wilcox (2007a), NCUA (2017a), FDIC (2017), FRB Chicago (2017), FFIEC (2017).

Failure rates computed across all credit unions vs. all commercial banks disguise the fact that failure rates are typically lower among credit unions than among commercial banks in similar asset size ranges. While institutions with under $100M in assets dominate the number of credit unions (at 99% in 1979 and 73% in 2016), they account for a far smaller proportion of credit union assets (at 63% in 1979 and 8% in 2010). Thus Figure 2 presents the annual evolution in 1980-2016 of a version of the failure rate weighted by assets, or of assets in institutions that fail during one year divided by assets in all institutions on the previous December 31 for both credit unions and commercial banks.[11]

11. Since this version of the failure rate uses data for individual institutions, the series begins in 1980 instead of 1971.

Figure 2

Percentage of Industry Assets in Failed Credit Unions and in Failed Commercial Banks, 1980-2016



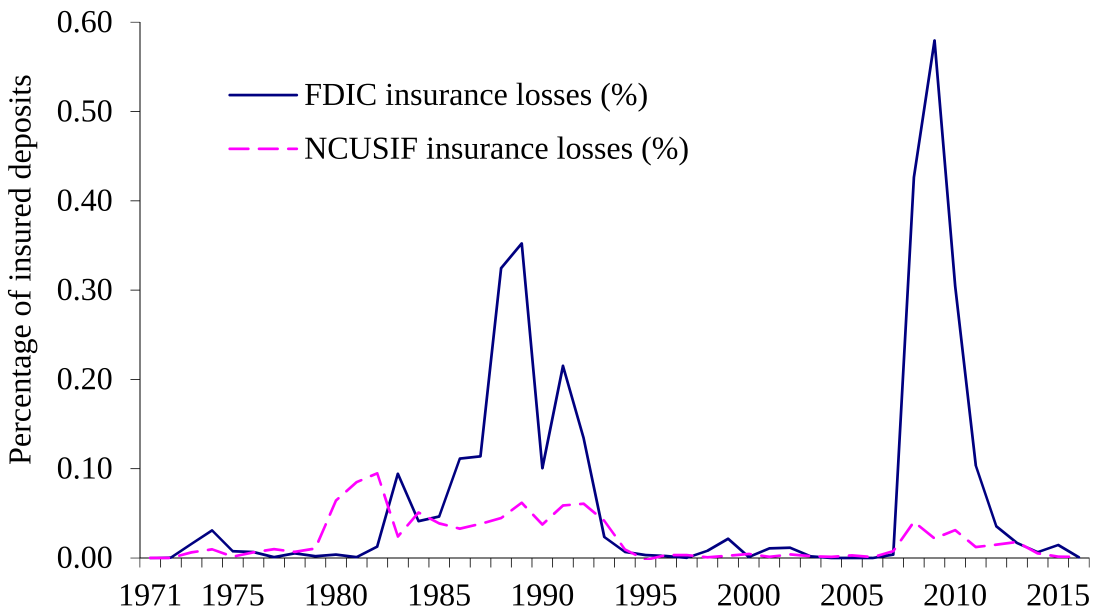
Sources: NCUA (2017a), FDIC (2017), FRB Chicago (2017), FFIEC (2017).

Correcting for the large number of smaller credit unions that hold a small proportion of assets (and their higher failure rates), Figure 2 displays size-adjusted failure rates for credit unions that are either similar or far lower than those for commercial banks in most years during this period. The annual failure rate of credit unions, when weighted by each credit union's assets, averaged 0.11% and peaked at 0.41% in 1991. In contrast, the annual commercial bank failure rate weighted by assets averaged 0.23% and peaked at 1.41% in 1988.

Figure 3 presents insurance losses per insured deposits during 1971-2016 for both the federal insurer for credit unions, the National Credit Union Share Insurance Fund (NCUSIF), and the federal insurer for commercial banks (and now thrifts). Consistent with the findings of Figure 2, insurance losses have been much larger at the FDIC than at the NCUSIF both in absolute terms and per insured deposits.[12] From 1971 to 2016, the FDIC reported total insurance losses of $107B ($146B in 2016 dollars). During this period, FDIC annual insurance losses per insured deposits averaged 0.07% and peaked at 0.58% in 2009. In contrast, NCUSIF insurance losses totaled $2.0B ($3.1B in 2016 dollars). NCUSIF annual insurance losses per insured deposits averaged 0.02% and peaked at 0.09% in 1982. Thus, the peak for NCUSIF insurance losses is about the same as the mean for FDIC insurance losses.

Figure 3

Deposit Insurance Loss Rates at the NCUSIF and at the FDIC, 1971-2016



Sources: Wilcox (2005), NCUA (2017a), FDIC (2017).

12. Wilcox (2005) also compares the annual evolution for both credit unions and commercial banks of different measures of insurance losses per assets in failing institutions during this period and finds them to be roughly similar.

4. Methodology

Thrift charters provide a natural experiment to test for the effects of the mutual vs. stock form of organization on issues such as efficiency, asset mix, and failure rates since (federal) mutual and stock thrifts have largely the same powers. Here we attempt to extend this type of analysis to other mutual[13] and stock financial institutions. However comparing failures of credit unions and commercial banks is more complex than comparing mutual and stock thrifts. Unlike among thrifts, the mix of assets and activities at credit unions may differ from those at commercial banks both (1) because their mutual structure affects their expense or asset preferences and (2) because legislation and regulation place more restrictive caps on credit union activities.[14] Thus we compare failures at credit unions and commercial banks while attempting to hold constant for several measures of their activities.

Since our dependent variable is binary in nature (survival or failure), and following the practice of much of the earlier literature, we used the logistic specification (logit) in our regressions.[15] Our dependent variable takes values of one for institutions failing and zero for institutions surviving within one calendar year. We pooled data across years in different periods for several reasons: (1) we are interested in fairly long-lived patterns and not one-off effects; (2) failures are relatively rare events and are absent in some individual years for many of our chosen subsamples; and (3) many earlier studies (e.g., Oshinsky and Olin 2004 and King et al. 2006) pool data across shorter and longer subperiods to explore the stability of coefficients. In

13. Credit union practitioners do not typically refer to their institutions as mutuals, preferring instead the term cooperative.
14. Of course, activity restrictions may not necessarily limit the ability of managers to seek higher-return riskier lending. For instance, some types of subprime, unsecured consumer lending permitted for credit unions could well involve higher interest rates and be riskier than many commercial loans permitted for commercial banks.
15. We also tested our models with OLS and found results to be broadly robust across both techniques. In our OLS specifications, we included state and year dummies and did not find them to change the coefficients and significance of our other included variables to a large extent.

particular, we compare three subperiods with high failures (failures in 1980-1986, 1987-1993, and 2008-2013) and two more quiescent subperiods with fewer failures (1994-2007 and 2014-2016). Following Kolari et al. (2001) and Kaufman (2004), we also explore the stability of coefficients across institutions with different asset sizes: tiny (with under $10M in assets), small ($10M-100M), medium ($100M-$1B), and large (over $1B), with all boundaries between asset sizes adjusted for inflation expressed in 2016 dollars.

We regressed whether an institution failed (=1) or survived (=0) during one calendar year (e.g., 2016) on financial data for each individual institution as of December 31 of the previous year (e.g., 2015).[16] Our choice of independent variables was dictated by (1) our literature review, (2) having to use variables reported somewhat consistently by both credit unions and commercial banks, and (3) the earliest dates on which those variables were available for both credit unions and commercial banks. We settled on an extended model with a longer list of variables that covers a shorter time period (i.e., failures in 1987-2016) and a basic model with a shorter list of the variables that were all available for an extended period of time (i.e., failures in 1980-2016).

In the basic model, we included the following independent variables: (1) asset size (expressed in 2016 dollars and logged) to control for possible effects of size on failure, (2) securities (and for credit unions other non-cash investments such as deposits in corporate credit unions), (3) residential mortgages,[17] as a measure of exposure to an asset often reported as linked to failures in credit unions, (4) loans other than residential mortgages, (5) all assets (e.g., branches, goodwill, etc.) other than securities, residential mortgages, loans other than residential

16. Rather than drop extreme outliers that might otherwise bias results, we used histograms for each variable in our models to guide our winsorizing our data. Thus, we turned extreme observations (e.g., ROAs below -15% or above 15%) into merely ones at the tail end of the relevant distribution.
17. Credit unions begin to report residential real estate loans other than first mortgages in 1986. We estimated the total of residential mortgages (i.e., firsts plus others) before then based on the relative weight of the two types, nationally, in 1986.

mortgages, and cash, i.e., we leave cash out as a common omitted variable against which other asset levels are compared, (6) provisions for loans losses, as an *ex post* measure of asset quality or risk, (7) capital per assets (net worth for credit unions and equity for commercial banks), (8) net income or return on assets (ROA), and (9) the unemployment rate in the previous year in the state in which the institution is headquartered, as a measure of local economic conditions.[18]

In the extended model, we dropped the variable "loans other than residential mortgages" and added instead (10) non-mortgage consumer loans,[19] (11) commercial and industrial (C&I) loans, (12) commercial mortgages,[20] and (13) noninterest expense, as a rough measure of efficiency. In the extended model, we also used (14) delinquent loans[21] instead of provisions for loan losses since the latter variable is likely more subject to managerial discretion (Wilcox and Stever 2007). Most of these variables (i.e., 2-8, 10-14) were expressed as a percentage of assets.

We performed our regressions for samples with only credit unions, with only commercial banks, and with both credit unions and commercial banks. We performed Chow tests to determine whether the same coefficients applied to both credit unions and commercial banks. When Chow tests failed, we regressed credit unions and commercial banks together using interaction terms (i.e., including additional variables that multiply each of the original variables by a credit union dummy variable). Regressions with interaction terms allow us to identify what

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18. Like Nuxoll (2003), we found our results to be broadly robust across models including and excluding the state unemployment rate. Since we used state unemployment rates in some of our models, we included throughout only credit unions and commercial banks headquartered in the fifty states and the District of Columbia, and not those in other U.S. territories.
19. Commercial banks begin to report consumer loans in 1984. Credit unions begin to report consumer loans in 1986. For credit unions, these include largely short-term unsecured consumer loans, credit card loans, and auto loans.
20. Credit unions begin to report business loans in 1986. For credit unions, data distinguishing C&I from commercial mortgages begins in 2004. For earlier years, we allocated credit union business loans as either C&I or commercial mortgages based on their relative weight, nationally, in 2004. Due to data limitations, we include agricultural loans not backed by real estate or land as C&I loans, and agricultural loans backed by real estate or land as commercial mortgages.
21. Delinquent loans and noninterest expense were first reported by commercial banks in 1984.

individual variables affect failures in credit unions and commercial banks in manners that are broadly similar or statistically different.

Once we have obtained estimates of coefficients (the betas), we do not only consider their sign, size, and statistical significance but also how the average characteristics (the X's) of credit unions and commercial banks differ. This would allow us, for instance, not only to know the impact of an additional percent of C&I loans on the likelihood of failure, but also how much of that type of risk each type of institution has accumulated on average. Lastly, we compare the distributions of estimated probabilities of failure implied by these betas and X's across various samples of credit unions and commercial banks. This approach allows us to consider succinctly not just how many institutions of each type actually failed, but also how much, according to our model, various types of institutions were at risk of failure.

5. Results: Failures, by Asset Size and by Subperiod

Tables 2 through 6 present results of logit regressions of failure on measures of the financial conditions for individual institutions and macroeconomic conditions. Table 2 presents results for extended models using a longer list of variables (e.g., ones that begin to be reported at a later date such as C&I loans and noninterest expenses), but for a shorter time period (failures in 1987-2016). Column 1 presents the results for a pooled sample of both credit unions and commercial banks, forcing a single set of coefficients for both types of institutions. The results are largely consistent with the earlier literature. Thus, the following are associated, all at the 1% level, with more failures: fewer securities, more commercial mortgages, more C&I loans, smaller asset size, more noninterest expense (i.e., lower efficiency), more delinquent loans, lower capital, lower ROA, and higher unemployment rates. The only variables that were not statistically associated with failure were consumer loans and residential mortgages.

Table 2:

Determinants of Failures of Credit Unions and of Commercial Banks, Pooled and Separately, 1987-2016

	Credit Unions and Commercial Banks (1)	Credit Unions Only (2)	Commercial Banks Only (3)	Difference (CU – CB) (4)
1. Constant	-2.78***	-1.97***	-1.76**	-0.22
	(-9.83)	(-5.11)	(-2.55)	(-0.27)
2. Securities	-0.02***	-0.01***	-0.02***	0.01**
	(-7.85)	(-4.36)	(-4.78)	(2.50)
3. Other assets (N.E.C.)	0.04***	0.06***	0.03***	0.02***
	(17.18)	(9.21)	(6.79)	(3.02)
4. Consumer loans	-0.0005	-0.002	0.01	-0.008
	(-0.30)	(-1.23)	(1.15)	(-1.45)
5. Residential mortgages	-0.004	0.006**	-0.01**	0.02***
	(-1.49)	(1.98)	(-2.38)	(3.05)
6. Commercial Mortgages	0.02***	0.05***	0.02***	0.03***
	(8.85)	(5.65)	(4.30)	(3.05)
7. C&I loans	0.02***	-0.01	0.02***	-0.03
	(7.88)	(-0.69)	(2.95)	(-1.45)
8. Log real assets	-0.17***	-0.23***	-0.13***	-0.10***
	(-10.22)	(-10.14)	(-4.58)	(-2.84)
9. Noninterest expenses	0.15***	0.19***	0.06***	0.13***
	(14.78)	(14.17)	(3.40)	(6.23)
10. Delinquent loans	0.20***	0.18***	0.20***	-0.01
	(46.47)	(31.25)	(25.31)	(-1.39)
11. Capital	-0.28***	-0.17***	-0.47***	0.30***
	(-44.77)	(-26.11)	(-39.96)	(22.26)
12. ROA	-0.10***	-0.08***	-0.11***	0.03**
	(-14.96)	(-8.66)	(-11.02)	(1.99)
13. Unemployment rate	0.14***	0.02	0.16***	-0.13***
	(12.11)	(1.14)	(8.87)	(-5.36)
14. Number of observations	571,187	302,919	268,268	
15. Number of failures	2,651	1,169	1,482	
16. Failure rate (%)	0.42	0.36	0.52	
17. R^2	0.20	0.12	0.32	

Note 1: *, **, and *** indicate significance at the 10%, 5%, and 1% level.

Note 2: Failure rates for multi-year periods are computed as the arithmetic averages of the annual failure rates in each multi-year period.

However, Chow test rejected the hypothesis that the same coefficients applied to both credit unions and commercial banks. Thus, we performed regressions for separate samples of only credit unions (column 2) and only commercial banks (column 3). We also performed a regression (column 4) with interaction-terms (i.e., variables obtained multiplying each original variable by a “dummy variable” that contains values of 1 for credit unions and values of 0 for commercial banks). The full set of results would involve twice as many coefficients and t-values, with half being identical to those for commercial banks in column 3, and another half referring to the interaction terms and reflecting the difference between the coefficients for credit unions and commercial banks and whether that difference is statistically significant. For simplicity, in column 4 we report only the coefficients and t’s for these differences.

While the same set of coefficients may not apply to both credit unions and commercial banks, many of the results were similar in that many variables had the same signs (i.e., positive or negative) and were significant for both types of institutions. For instance, the following were associated, all at the 1% level, with more failures: fewer securities, more commercial mortgages, smaller asset size, higher noninterest expenses, more delinquent loans, lower capital, and lower ROAs.

As the Chow test implied, not all results were consistent. For instance, more residential mortgages were associated with more failures of credit unions, but not of commercial banks. In contrast, more C&I loans were associated with more failures of commercial banks, but not of credit unions. These results might point to the benefits of shifting assets to diversify each type of lender. Thus shifting credit unions’ assets away from residential mortgages and toward C&I

loans might reduce their failures; and the converse shift from C&I loans to residential mortgages might reduce failures in commercial banks.

Another difference is that our indicator of macroeconomic conditions (the state-level unemployment rate) was significant for commercial banks, but not for credit unions.

The results in column 4 also highlight that while most coefficients have the same sign for credit unions and commercial banks, few of those coefficients have similar sizes. For instance, commercial banks' coefficient for capital is three times as large as that for credit unions. Overall, only four of thirteen coefficients had a statistically similar size.

Comparing the R^2's for credit unions and commercial banks, we explain far larger proportions of the variation for commercial banks than for credit unions. This is consistent with the findings of Gordon et al. (1987) and Shafroth (1997) that many failures in credit unions take place for largely idiosyncratic reasons (such as sponsor failures, poor record keeping, etc.) that are unrelated to the historical financial conditions of the individual institutions.

Thus, while models of institutional failure in credit unions and commercial banks may be broadly similar, there are substantial differences that require findings and conclusions drawn from one type of institution to be applied only with caution to the other type of institution.

Table 3 explores whether the pattern of coefficient signs and significance levels varies substantially across asset size ranges. In particular, we examined tiny institutions (with under $10M in assets), smallish ones ($10M-$100M), medium ones ($100M-$1B), and large ones (over $1B), with all boundaries between asset sizes adjusted for inflation expressed in 2016 dollars. We chose our asset size boundaries largely to be able to focus on two roughly-comparable asset size groups common to both credit unions and commercial banks. Thus, the tiny group separates many credit unions, and their failures, into a group that is largely irrelevant for commercial banks. Similarly, the large group separates many commercial banks, and their failures, into a group that is only relatively new for credit unions, and for which there has been only one failure (of a large credit union) in three decades.[22]

By and large, many results were broadly consistent. For instance, more failures were associated with more delinquent loans, lower capital, and lower ROAs for all asset sizes and types of institutions. While we found no clear links between asset size and what variables tended to be significant, our results likely imply that models should be used across asset size ranges. Not only do the sizes of estimated coefficients vary widely, but the fractions of variation explained by models differs widely across asset sizes from 0.12 for tiny institutions to 0.18 for smallish ones and 0.31 for medium ones.

Table 4 then explores whether the pattern of coefficient signs and significance levels vary substantially across subperiods. In particular, we examined two subperiods with many failures (1987-1993 and 2008-2013) and two more quiescent subperiods (1994-2007 and 2014-2016).

Some results are broadly consistent across time periods and types of institutions. For instance, more failures were associated, always at the 1% level, with more delinquent loans and less capital for all time periods and types of institutions. However, we found several substantial differences both across subperiods and types of institution. For instance, the percentages of variation explained (R^2) were substantially lower for credit unions across all subperiods (0.12, 0.15, 0.08, and 0.04) than for commercial banks (0.37, 0.09, 0.28, and 0.24), likely highlighting that credit union failures tend to be more idiosyncratic, or harder to predict. Moreover, while commercial bank models explained a larger fraction of the variation during high-failure periods, credit union R^2's were not clearly associated with failure rates.

22. Since there has been only one failure of a large natural person credit unions in 1980-2016, we do not include regression results for large credit unions.

Table 3:

Determinants of Failures of Credit Unions and of Commercial Banks, by Size, 1987-2016

	Credit Unions				Commercial Banks			
	Tiny (1)	Smallish (2)	Medium (3)	Large (4)	Tiny (5)	Smallish (6)	Medium (7)	Large (8)
1. Constant	-3.89***	3.26	50.56***		-21.55*	2.74	-5.34***	-3.48
	(-7.80)	(1.20)	(3.68)		(-1.84)	(1.61)	(-2.80)	(-1.06)
2. Securities	-0.007***	-0.002	-0.09***		0.04*	-0.03***	-0.02**	-0.01
	(-3.07)	(-0.20)	(-2.83)		(1.92)	(-4.87)	(-2.26)	(-0.78)
3. Other assets (N.E.C.)	0.05***	0.11***	0.10		0.02	0.01	0.05***	0.04***
	(8.52)	(4.79)	(1.61)		(0.68)	(1.26)	(5.77)	(2.64)
4. Consumer loans	-0.003*	-0.005	-0.05**		-0.03	0.001	0.01	-0.07**
	(-1.94)	(-0.71)	(-2.08)		(-0.96)	(0.14)	(1.13)	(-2.17)
5. Residential mortgages	0.003	0.008	0.003		0.02	-0.005	-0.01	-0.03
	(0.81)	(1.12)	(0.18)		(0.83)	(-0.61)	(-1.37)	(-1.40)
6. Commercial Mortgages	0.07***	0.04	0.08***		-0.07	0.005	0.03***	0.04***
	(3.47)	(0.89)	(2.76)		(-1.09)	(0.61)	(3.75)	(2.76)
7. C&I loans	-0.03	-0.04	-0.29***		0.01	0.02**	0.02*	-0.02
	(-0.85)	(-0.42)	(-3.23)		(0.33)	(2.53)	(1.90)	(-1.07)
8. Log real assets	-0.10***	-0.56***	-2.80***		0.85	-0.37***	0.08	-0.03
	(-3.18)	(-3.55)	(-3.75)		(1.14)	(-3.89)	(0.85)	(-0.22)
9. Noninterest expenses	0.20***	0.30***	0.46**		0.27***	0.11***	-0.07**	-0.004
	(14.39)	(5.64)	(2.16)		(3.28)	(4.81)	(-2.45)	(-0.06)
10. Delinquent loans	0.18***	0.23***	0.21***		0.18***	0.18***	0.17***	0.23***
	(29.54)	(8.82)	(3.61)		(3.34)	(15.84)	(13.18)	(7.84)
11. Capital	-0.14***	-0.39***	-0.38***		-0.14***	-0.52***	-0.51***	-0.34***
	(-21.31)	(-15.47)	(-6.61)		(-4.47)	(-30.96)	(-23.94)	(-7.46)
12. ROA	-0.06***	-0.16***	-0.27***		-0.09*	-0.06***	-0.21***	-0.11**
	(-6.24)	(-4.66)	(-2.97)		(-1.73)	(-4.16)	(-11.01)	(-2.00)
13. Unemployment rate	0.009	0.08*	-0.27**		0.30*	0.21***	0.10***	0.08
	(0.44)	(1.84)	(-2.22)		(1.83)	(7.70)	(3.76)	(1.26)
14. Number of observations	156,384	112,028	31,417	3,090	2,402	122,752	126,599	16,515
15. Num. of failures	949	182	37	1	18	760	592	109
16. Failure rate (%)	0.53	0.17	0.13	0.02	0.65	0.50	0.47	0.64
17. R^2	0.12	0.18	0.31		0.05	0.36	0.31	0.25

Note 1: all boundaries between asset sizes are adjusted for inflation, expressed in 2016 dollars. Tiny institutions have fewer than $10 million (M) in assets, smallish have $10-100M, medium have $100M - $1 billion (B), and large+ have more than $1B.
Note 2: *, **, and *** indicate significance at the 10%, 5%, and 1% level.
Note 3: Failure rates for multi-year periods are computed as the arithmetic averages of the annual failure rates in each multi-year period.

Table 4

Determinants of Failures of Credit Unions and of Commercial Banks, by Subperiods, 1987-2016

	Credit Unions				Commercial Banks			
	1987-1993 (1)	1994-2007 (2)	2008-2013 (3)	2014-2016 (4)	1987-1993 (5)	1994-2007 (6)	2008-2013 (7)	2014-2016 (8)
1. Constant	-3.62***	-0.002	-0.88	4.12***	1.84*	-5.72**	-6.33***	12.86**
	(-6.98)	(0.003)	(-0.78)	(2.28)	(1.96)	(-2.05)	(-5.13)	(2.14)
2. Securities	-0.003	-0.02***	-0.04***	0.02	-0.03***	-0.07***	0.001	-0.03
	(-1.14)	(-3.40)	(-4.62)	(1.52)	(-4.25)	(-2.82)	(0.08)	(-0.93)
3. Other assets (N.E.C.)	0.06***	0.05***	0.07***	0.09***	0.03***	0.004	0.05***	-0.001
	(7.01)	(5.64)	(3.24)	(2.61)	(5.27)	(0.17)	(5.12)	(-0.05)
4. Consumer loans	-0.0002	0.003	-0.02***	-0.005	0.01	-0.02	-0.08**	0.08*
	(-0.09)	(0.66)	(-2.96)	(-0.44)	(1.48)	(-0.73)	(-2.53)	(1.92)
5. Residential mortgages	0.009***	0.006	-0.02**	0.02	-0.004	0.004	-0.006	-0.01
	(2.33)	(0.82)	(-1.98)	(1.35)	(-0.55)	(0.19)	(-0.66)	(-0.39)
6. Commercial Mortgages	0.04***	0.08***	0.03*	0.06*	0.008	-0.02	0.03***	0.02
	(4.70)	(3.13)	(1.76)	(1.77)	(1.16)	(-0.96)	(3.13)	(0.57)
7. C&I loans		-0.05	-0.06	0.02	0.02***	0.02	0.001	0.005
		(-0.97)	(-1.06)	(0.75)	(2.56)	(1.14)	(0.12)	(0.11)
8. Log real assets	-0.15***	-0.35***	-0.11	-0.63***	-0.27***	-0.01	0.11**	-0.76**
	(-4.87)	(-6.78)	(-1.50)	(-5.59)	(-6.89)	(-0.10)	(2.35)	(-2.47)
9. Noninterest expenses	0.26***	0.11***	0.05	0.16**	-0.007	0.24***	0.005	0.12
	(14.82)	(3.94)	(1.14)	(2.44)	(-0.32)	(4.48)	(0.15)	(0.93)
10. Delinquent loans	0.19***	0.16***	0.20***	0.13***	0.20***	0.14***	0.18***	0.15**
	(25.47)	(11.86)	(9.16)	(3.25)	(15.81)	(4.53)	(12.44)	(2.44)
11. Capital	-0.15***	-0.17***	-0.19***	-0.11***	-0.56***	-0.23***	-0.24***	-0.80***
	(-16.28)	(-12.74)	(-8.03)	(-3.90)	(-33.47)	(-5.46)	(-11.55)	(-7.35)
12. ROA	-0.09***	-0.12***	-0.11***	-0.09*	-0.07***	-0.31***	-0.25***	-0.15
	(-6.77)	(-6.14)	(-3.17)	(-1.68)	(-5.56)	(-6.41)	(-9.37)	(-0.94)
13. Unemployment rate	-0.008	-0.04	-0.06	-0.12	0.13***	0.06	-0.05*	-0.01
	(-0.32)	(-0.66)	(-1.53)	(-0.90)	(4.93)	(0.66)	(-1.66)	(-0.06)
14. Number of observations	94,266	145,287	44,585	18,781	88,197	121,740	40,391	16,940
15. Num. of failures	741	264	119	45	979	58	418	27
16. Failure rate (%)	0.79	0.18	0.27	0.24	1.07	0.05	1.02	0.16
17. R^2	0.12	0.15	0.08	0.04	0.37	0.09	0.28	0.24

Note 1: *, **, and *** indicate significance at the 10%, 5%, and 1% level.
Note 2: Failure rates for multi-year periods are computed as the arithmetic averages of the annual failure rates in each multi-year period.

Interpreting changes in the significance of variables is complex. Which changes might reflect enduring shifts in our financial landscape? Or which ones might reflect one-time effects during unusual times, such as the financial crisis, that might not be likely to be repeated? For instance, during the earlier high-failure period, more residential mortgages were associated with more credit union failures. In contrast, during the more recent high-failure period, more residential mortgages were associated with fewer credit union failures.

In a further example, during the earlier high-failure period, more securities were associated with fewer commercial bank failures. In contrast, during the more recent high-failure period, more securities were associated with more commercial bank failures. This change might reflect either or both changes in the composition of their holdings of securities (e.g., shifting from Treasurys to mortgage-backed securities, MBS) or simply changes in their performance (i.e., MBS performing more poorly during the crisis than during earlier periods).

Similarly, smaller size was consistently associated with more credit union failures during most subperiods, but not during the financial crisis. Among commercial banks, smaller size was associated with more commercial bank failures during the earlier high-failure period and during the most recent post-crisis period. However, during the financial crisis, it was actually larger size that was associated with more commercial bank failures.

Table 5 dissects our results further by moving beyond breaking down our subsamples by either of asset size or by subperiod. Instead, we provide an example of results broken down by subperiods for one asset size group (smallish institutions). We do not show results by subperiod for all asset size groups since dissecting further and further, one quickly encounters detailed subsamples with too few failures to meaningfully perform regressions. For instance, there were only three failures of medium credit unions during 1994-2007. Briefly, many of the results in

Table 5 largely confirm those from other subsamples. For instance, more failures are most often associated with, as usual, more delinquent loans, less capital, and less ROA.

Finally, Table 6 presents results for basic models using the smaller set of variables for which all data was available for an extended period of time (failures in 1980-2016). Columns 1 and 5 present results for credit unions and commercial banks. Columns 2-3 and 6-7 reproduce the same model for the earlier additional years (1980-1986) and for the same period as in Table 2 (1987-2016). For ease of comparison, columns 4 and 8 replicate the extended models using the larger set of variables already presented in Table 2. While the pattern of coefficients and levels of significance is not identical across the basic and extended models, much of the overall pattern is largely consistent. Examples of consistent results include, as usual, that more failures are associated with smaller size, more delinquencies (or provisions for loan losses), less capital, and lower ROA.

Table 5

Determinants of Failures of Smallish Credit Unions and of Smallish Commercial Banks, by Subperiods, 1987-2016

	Smallish Credit Unions				Smallish Commercial Banks			
	1987-1993	1994-2007	2008-2013	2014-2016	1987-1993	1994-2007	2008-2013	2014-2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Constant	10.19***	-7.52	1.86	-21.53	5.11***	-2.56	-3.65	10.35
	(2.67)	(-1.14)	(0.31)	(-1.15)	(2.57)	(-0.34)	(-0.75)	(0.80)
2. Securities	0.02	-0.05**	-0.04**	-0.09***	-0.03***	-0.09**	-0.02	-0.01
	(1.41)	(-2.16)	(-1.97)	(-2.69)	(-3.79)	(-2.35)	(-1.64)	(-0.27)
3. Other assets (N.E.C.)	0.13***	0.05	0.12**	-0.86**	0.004	0.001	0.02	0.03
	(4.25)	(0.87)	(2.47)	(-2.14)	(0.38)	(0.02)	(1.22)	(0.87)
4. Consumer loans	0.004	-0.006	-0.07***	-0.15***	0.01	0.01	-0.06	0.12**
	(0.42)	(-0.36)	(-3.37)	(-3.12)	(1.21)	(0.16)	(-1.41)	(2.11)
5. Residential mortgages	0.03***	-0.01	-0.05***	-0.22**	0.002	0.02	-0.01	0.01
	(2.68)	(-0.47)	(-2.73)	(-2.46)	(0.24)	(0.51)	(-0.46)	(0.21)
6. Commercial Mortgages	0.03	0.17	0.02	0.003	0.02	0.001	0.003	0.01
	(1.20)	(1.08)	(0.34)	(0.03)	(1.54)	(-0.02)	(-0.19)	(0.25)
7. C&I loans		-0.43	-0.05	-0.17	0.02***	0.04	0.003	-0.02
		(-1.26)	(-0.67)	(-0.95)	(2.58)	(1.17)	(-0.17)	(-0.32)
8. Log real assets	-1.01***	0.139	-0.13	1.52	-0.47***	-0.12	-0.10	-0.64
	(-4.55)	(0.35)	(-0.37)	(1.36)	(-4.30)	(-0.29)	(-0.34)	(-0.89)
9. Noninterest expenses	0.34***	0.114	0.10	0.48**	0.01	0.25***	0.28***	0.20
	(4.16)	(0.76)	(0.85)	(2.17)	(0.35)	(3.03)	(4.80)	(1.27)
10. Delinquent loans	0.15***	0.41***	0.25***	0.85***	0.21***	0.11***	0.17***	0.18**
	(4.35)	(7.49)	(3.41)	(3.52)	(12.88)	(2.56)	(5.39)	(2.29)
11. Capital	-0.44***	-0.39***	-0.41***	-0.27	-0.58***	-0.35***	-0.14***	-0.73***
	(-10.83)	(-5.61)	(-5.13)	(-1.18)	(-27.10)	(-5.01)	(-4.94)	(-5.22)
12. ROA	-0.11**	-0.22***	-0.18**	0.078	-0.04***	-0.37***	-0.09*	-0.22
	(-2.24)	(-2.83)	(-2.00)	(0.25)	(-2.97)	(-5.02)	(-1.94)	(-1.14)
13. Unemployment rate	0.07	0.14	0.01	-0.01	0.18***	-0.21	0.10	-0.27
	(1.05)	(0.84)	(0.12)	(-0.02)	(5.06)	(-1.48)	(1.63)	(-0.94)
14. Number of observations	27,669	56,557	19,405	8,397	49,309	55,281	13,294	4,868
15. Num. of failures	114	31	31	6	636	30	78	16
16. Failure rate (%)	0.41	0.05	0.16	0.07	1.25	0.05	0.60	0.32
17. R^2	0.20	0.21	0.13	0.38	0.41	0.16	0.13	0.29

Note 1: Smallish institutions have assets of $10-100M. All boundaries between asset sizes are adjusted for inflation, expressed in 2016 dollars.
Note 2: *, **, and *** indicate significance at the 10%, 5%, and 1% level.
Note 3: Failure rates for multi-year periods are computed as the arithmetic averages of the annual failure rates in each multi-year period.

Table 6: Determinants of Failures of Credit Unions and Commercial Banks, by Subperiods, 1980-2016

	Credit Unions				Commercial Banks			
	1980-2016 (1)	1980-1986 (2)	1987-2016 (3)	1987-2016 (4)	1980-2016 (5)	1980-1986 (6)	1987-2016 (7)	1987-2016 (8)
1. Constant	2.29***	3.29***	1.86***	-1.97***	-1.82***	3.68**	-2.58***	-1.76**
	(10.11)	(10.86)	(5.28)	(-5.11)	(-3.23)	(2.55)	(-4.34)	(-2.55)
2. Securities	-0.01***	-0.01***	-0.002	-0.01***	-0.01***	0.00	-0.02***	-0.02***
	(-3.17)	(-3.01)	(-0.64)	(-4.36)	(-2.66)	(0.97)	(-4.31)	(-4.78)
3. Other assets (N.E.C.)	0.02***	0.01***	0.09***	0.06***	0.04***	0.04***	0.04***	0.03***
	(7.53)	(4.45)	(14.6)	(9.21)	(8.96)	(3.22)	(6.93)	(6.79)
4. Consumer loans				-0.002				0.01
				(-1.23)				(1.15)
5. Residential mortgages	0.03***	0.03***	0.04***	0.006**	0.01**	0.01	-0.003	-0.01**
	(14.02)	(6.93)	(11.37)	(1.98)	(1.99)	(1.06)	(-0.53)	(-2.38)
6. Commercial Mortgages				0.05***				0.02***
				(5.65)				(4.30)
7. C&I loans				-0.01				0.02***
				(-0.69)				(2.95)
8. Non-residential loans	0.02***	0.02***	0.03***		0.05***	0.10***	0.03***	
	(11.67)	(8.45)	(11.20)		(10.88)	(10.67)	(5.50)	
9. Log real assets	-0.48***	-0.57***	-0.53***	-0.23***	-0.21***	-0.67***	-0.11***	-0.13***
	(-35.14)	(-25.88)	(-25.67)	(-10.14)	(-9.33)	(-10.82)	(-4.59)	(-4.58)
10. Noninterest expenses				0.19***				0.06***
				(14.17)				(3.40)
11. Loan loss provisions	0.13***	0.09***	0.10***		0.12***	-0.03	0.15***	
	(11.03)	(5.42)	(5.97)		(9.14)	(-0.60)	(9.84)	
12. Delinquent loans				0.18***				0.20***
				(31.25)				(25.31)
13. Capital	-0.16***	-0.14***	-0.19***	-0.17***	-0.53***	-0.50***	-0.51***	-0.47***
	(-30.84)	(-16.87)	(-26.91)	(-26.11)	(-49.90)	(-17.64)	(-43.00)	(-39.96)
14. ROA	-0.11***	-0.07***	-0.14***	-0.08***	-0.14***	-0.24***	-0.14***	-0.11***
	(-10.62)	(-5.12)	(-8.83)	(-8.66)	(-14.84)	(-5.34)	(-14.51)	(-11.02)
15. Unemployment rate	-0.07***	-0.09***	0.06***	0.02	0.16***	0.09***	0.25***	0.16***
	(-6.42)	(-5.20)	(3.26)	(1.14)	(12.66)	(3.64)	(15.25)	(8.87)
14. Number of observations	416,771	113,852	302,919	302,919	369,009	100,733	268,268	268,268
15. Num. of failures	2,165	996	1,169	1,169	1,904	422	1,482	1,482
16. Failure rate (%)	0.44	0.86	0.36	0.36	0.48	0.42	0.52	0.52
17. R^2	0.06	0.04	0.09	0.12	0.25	0.13	0.30	0.32

Note 1: *, **, and *** indicate significance at the 10%, 5%, and 1% level.

Note 2: Failure rates for multi-year periods are computed as the arithmetic averages of the annual failure rates in each multi-year period.

6. Data for Determinants of Failure and Estimated Probabilities of Failure (EPFs)

Tables 2 through 6 presented the coefficients (the betas) for variables in regressions modeling failures of credit unions and commercial banks. Table 7 presents averages of the values in those variables (the X's). Columns 1 and 6 present averages for credit unions and commercial banks. Columns 2-5 and 7-10 present averages for tiny (under $10M in assets), smallish ($10M-$100M), medium ($100M-$1B), and large (over $1B) institutions, with all boundaries between asset sizes adjusted for inflation expressed in 2016 dollars. For ease of exposition, Panel A replicates part of Table 1, presenting the number of institutions across asset sizes on several representative years.

The numbers of both credit unions and commercial banks have shrunk massively during this period, but the pattern of those changes differs markedly across types of institution. Among credit unions, the bulk of the reduction has taken place among tiny institutions whose numbers have fallen from 14,526 to, a still rather large number of 1,659. In contrast, the numbers of both medium and of large credit unions have increased markedly, respectively from 289 to 1,279 and from 3 to 272. The number of smallish credit unions has largely been stable, in large part as many tiny credit unions grew, or merged, into smallish institutions. In contrast, among commercial banks, the number of tiny institutions was never large, falling from 259 to 29, and the bulk of the reduction took place among smallish institutions, whose numbers fell from 8,695 to 1,371. Unlike among credit unions, the numbers of both medium and large commercial banks have been roughly stable during this period.

Table 7: Descriptive Statistics for Credit Unions and for Commercial Banks, Percentage of Assets (%), by Size, by Subperiods, 1979-2016

	Credit Unions					Commercial Banks				
	All (1)	Tiny (2)	Smallish (3)	Medium (4)	Large (5)	All (6)	Tiny (7)	Smallish (8)	Medium (9)	Large (10)
A. Number of institutions										
1. 1979	17,482	14,526	2,664	289	3	14,355	259	8,695	4,927	473
2. 1986	14,693	10,232	3,790	647	17	14,171	169	7,863	5,538	594
3. 1993	12,317	7,089	4,309	880	36	10,960	83	5,734	4,583	560
4. 2007	8,101	3,364	3,388	1,200	148	7,356	81	2,675	4,011	589
5. 2013	6,554	2,138	2,921	1,273	217	5,911	37	1,768	3,553	553
6. 2016	5,785	1,659	2,575	1,279	272	5,163	29	1,371	3,157	606
B. Assets ($ Billion, 2016 Dollars)										
7. 1979	169	32	75	58	4.9	5,325	2.0	420	1,193	3,710
8. 1986	323	28	117	149	29	6,420	1.2	396	1,388	4,635
9. 1993	459	24	139	222	74	6,139	0.6	301	1,148	4,690
10. 2007	866	13	119	358	376	12,856	0.5	147	1,183	11,525
11. 2013	1,100	8.7	109	391	592	14,159	0.2	104	1,070	12,984
12. 2016	1,293	6.8	97	395	793	15,639	0.2	82	998	14,558
C. Percentage of Industry Assets in each Asset Group										
13. 1979	100	19	44	34	2.9	100	0.04	7.9	22	70
14. 1986	100	8.7	36	46	9.0	100	0.02	6.2	22	72
15. 1993	100	5.2	30	48	16	100	0.01	4.9	19	76
16. 2007	100	1.5	14	41	43	100	0.004	1.1	9.2	90
17. 2013	100	0.8	10	36	54	100	0.002	0.7	7.6	92
18. 2016	100	0.5	7.5	31	61	100	0.001	0.5	6.4	93
D. Cash										
19. 1979-1986	13	11	15	14	11	15	13	9.1	9.9	17
20. 1987-1993	12	16	16	8.9	8.6	9.7	16	7.8	6.7	11
21. 1994-2007	7.7	15	11	6.7	6.1	5.9	15	5.7	4.6	6.1
22. 2008-2013	8.3	16	11	8.5	7.4	9.3	27	11	7.6	9.5
23. 2014-2016	7.7	14	9.3	7.8	7.3	12	33	13	7.7	12
24. 1979-2016	9.7	14	12	9.0	8.0	9.5	18	8.2	6.8	10
E. Securities										
25. 1979-1986	16	14	15	19	16	17	36	30	27	12
26. 1987-1993	25	20	21	28	30	19	28	31	28	16
27. 1994-2007	24	23	23	24	26	18	24	26	24	17
28. 2008-2013	25	32	31	24	24	17	33	21	18	17
29. 2014-2016	23	36	34	23	21	20	36	24	21	20
30. 1979-2016	23	23	23	24	24	18	30	27	24	16
F. Consumer Loans										
31. 1987-1993	34	48	36	31	29	12	10	10	11	12
32. 1994-2007	34	49	38	34	30	10	8.0	7.5	7.3	11
33. 2008-2013	26	39	28	26	24	9.1	2.2	4.3	3.2	10
34. 2014-2016	29	39	28	29	28	9.1	1.8	4.0	2.8	10
35. 1987-2016	32	46	35	31	29	10	7.0	7.5	7.5	11
G. Residential Mortgages										
36. 1979-1986	8.1	2.5	6.9	11	11	7.5	6.8	11	11	6
37. 1987-1993	20	5.7	16	23	23	12	9.8	14	16	10
38. 1994-2007	26	5.7	19	26	31	16	9.1	16	18	15
39. 2008-2013	30	6.3	21	29	34	17	6.6	15	16	17
40. 2014-2016	29	5.1	19	26	32	14	5.7	15	17	14
41. 1979-2016	22	5.1	16	23	26	13	8.1	14	16	13

Table 7 (continued)

Descriptive Statistics for Credit Unions and for Commercial Banks, Percentage of Assets (%), by Size, by Subperiods, 1979-2016

	Credit Unions					Commercial Banks				
	All (1)	Tiny (2)	Smallish (3)	Medium (4)	Large (5)	All (6)	Tiny (7)	Smallish (8)	Medium (9)	Large (10)
H. Commercial Mortgages										
42. 1987-1993	0.5	0.2	0.5	0.6	0.5	12	4.9	11	14	11
43. 1994-2007	1.0	0.2	0.5	1.3	0.9	12	8.0	18	25	11
44. 2008-2013	3.2	0.1	1.0	3.6	3.5	12	3.9	20	31	10
45. 2014-2016	3.9	0.1	1.1	4.2	4.2	11	1.3	14	28	10
46. 1987-2016	1.6	0.2	0.7	1.8	1.7	11	5.4	15	21	9.9
I. C&I Loans										
47. 1987-1993	0.3	0.1	0.2	0.3	0.2	18	13	16	14	20
48. 1994-2007	0.5	0.1	0.3	0.6	0.3	15	13	17	13	15
49. 2008-2013	0.8	0.2	0.5	1.1	0.7	11	4.6	15	12	11
50. 2014-2016	0.9	0.3	0.6	1.3	0.8	12	1.7	13	12	12
51. 1987-2016	0.5	0.1	0.4	0.7	0.4	16	12	17	14	17
J. Noninterest Expenses										
52. 1987-1993	3.02	3.67	3.29	2.92	2.33	3.47	12.16	3.47	3.30	3.52
53. 1994-2007	3.16	3.84	3.70	3.32	2.46	3.31	19.12	3.51	3.29	3.31
54. 2008-2016	3.19	4.08	3.88	3.58	2.71	2.90	44.68	4.14	3.16	2.86
55. 2014-2016	3.01	3.73	3.57	3.48	2.67	2.60	39.96	4.19	3.01	2.56
56. 1987-2016	3.15	3.89	3.58	3.20	2.55	3.18	23.19	3.66	3.23	3.17
K. Provisions for Loans Losses										
57. 1979-1986	0.40	0.46	0.39	0.39	0.41	0.88	1.62	0.58	0.56	0.99
58. 1987-1993	0.39	0.47	0.39	0.38	0.36	0.84	1.52	0.46	0.49	0.96
59. 1994-2007	0.34	0.40	0.31	0.34	0.34	0.41	-0.09	0.24	0.27	0.44
60. 2008-2013	0.63	0.41	0.42	0.57	0.74	0.92	0.01	0.38	0.63	0.96
61. 2014-2016	0.33	0.31	0.25	0.30	0.36	0.22	0.01	0.12	0.12	0.23
62. 1979-2016	0.38	0.40	0.33	0.36	0.42	0.56	0.35	0.36	0.39	0.60
L. Capital (Net worth or equity)										
63. 1979-1986	7.20	9.34	7.49	6.86	6.37	6.49	24.99	9.14	7.91	5.89
64. 1987-1993	7.60	9.63	7.87	7.32	6.79	6.75	24.98	9.31	8.14	6.18
65. 1994-2007	10.91	14.33	11.96	10.89	9.91	8.98	36.34	11.63	9.80	8.76
66. 2008-2013	10.35	15.24	11.92	10.51	9.73	10.88	60.13	12.34	10.42	10.91
67. 2014-2016	10.93	15.05	11.90	10.98	10.73	11.19	66.59	12.69	11.07	11.19
68. 1979-2016	9.29	12.43	10.11	9.08	8.25	8.41	37.40	10.84	9.22	8.05
M. ROA (return on assets, or net income)										
69. 1979-1986	0.96	0.95	0.91	0.99	0.96	0.57	0.86	0.67	0.81	0.50
70. 1987-1993	1.02	0.98	0.96	1.05	1.08	0.63	1.14	0.68	0.86	0.57
71. 1994-2007	0.94	0.71	0.81	0.94	1.03	1.18	2.84	0.94	1.18	1.18
72. 2008-2013	0.41	-0.12	0.16	0.34	0.52	0.64	5.50	0.52	0.52	0.65
73. 2014-2016	0.75	0.04	0.34	0.61	0.89	1.00	7.19	0.96	1.03	1.00
74. 1979-2016	0.86	0.67	0.73	0.82	0.88	0.88	2.78	0.82	0.95	0.85

Note: all boundaries between asset sizes are adjusted for inflation, expressed in 2016 dollars. Tiny institutions have fewer than $10 million (M) in assets, smallish have $10-100M, medium have $100M - $1 billion (B), and large have more than $1B.

Panel B presents the equivalent data for assets and Panel C present the percentage of assets in each asset size group in each year. The data presented highlight that credit unions are a far smaller, but growing, segment of the U.S. depository industry, with total assets in credit unions growing from 4% as many as those in commercial banks in 1979 to 8% in 2016. The shifts in the distributions of assets across asset sizes also differ markedly between credit unions and commercial banks. Among credit unions, tiny and smallish institutions once held sizable shares of assets (19% and 44% in 1979) and large ones held very few (3%). Over time, tiny and smallish credit unions have come to hold far smaller fractions (0.5% and 7.5% in 2016) and large ones more than half of credit union assets (61%). In contrast, large banks (i.e., using our credit union-centric definition of over $1B of assets) have simply increased their share from very large (70% in 1979) to very, very large (93% in 2016).

In the remaining panels, variables are presented as a percentage of assets. For each variable, we present averages for several subperiods. When all the data was available for both types of institutions, we included the subperiod of failures in 1979-1986. For all variables, we include two subperiods with many failures (1987-1993 and 2008-2013) and two subperiods with fewer failures (1994-2007 and 2014-2016). Subperiod averages were computed as follows: First we computed annual averages (weighted by assets). Next we computed and report simple arithmetic averages across the annual values included in each subperiod.

Tables 2 through 7 together highlight the difficulties in trying to assess whether one type of institution is inherently riskier than the other. Our results point out what types of activities could make either credit unions or commercial banks more prone to failure, but they do not point to either institution being more or less at risk for all combinations of activities. For instance, comparing a credit union A and a commercial bank B with identical characteristics and both with many residential mortgages, one might conclude the credit union was more likely to fail. Comparing a separate pair of credit union C and commercial bank D, again identical to each other, and both with many C&I loans, one might conclude the commercial bank was more likely to fail. Thus our findings provide guidance on how individual institutions might reduce their risk of failure, but do not help to answer whether either type of institution is inherently more or less prone to failure. Rather each individual institution might be able to change its risk level by tailoring its portfolio of activities.

Table 7 shows that the levels of commercial mortgages, C&I loans, provisions for loan losses, and capital at commercial banks would imply that on average they have a riskier profile than credit unions. Commercial mortgage and C&I loans, variables often identified in our models and in the literature as particularly risk-prone, appear as the clearest difference between credit unions and commercial banks. Commercial mortgages and C&I loans are almost a footnote, even if a growing one, for credit unions (at 3.9% and 0.9% of assets), but are substantial portions, even if somewhat shrinking ones, of the portfolios of commercial banks (at 11% and 12%).

Over extended periods of time, credit unions have reported substantially lower provisions for loan losses than commercial banks (0.38% vs. 0.56%). Whereas provisions for loan losses may be manipulated by management in the short-term (Wilcox and Stever 2007), it is unlikely that this manipulation can hide differences in asset risk over the long term. Thus, credit union loans would have been less risky that commercial bank loans. (Examining delinquent loans yields broadly similar results.)

In contrast, the levels of other variables such as residential mortgages and asset size would imply that on average credit unions have riskier profiles than commercial banks. Credit unions have traditionally been and remain far smaller than commercial banks and, thus, on average often reflect the traditionally higher failure rates of smaller institutions. Combining the coefficients from the models for smallish and medium credit unions and commercial banks for 1987-2016 (models 2-3 and 6-7 in Table 3) and data for individual institutions, we may generate the estimated probability of failure (EPF) for individual institutions and graph EPF distributions.

Table 8

Distributions of Estimated Probabilities of Failure (EPFs) of Credit Unions and of Commercial Banks, by Size, 1990, 2000, 2010, and 2017

	Under 0.0001% (1)	0.0001% -0.001% (2)	0.001% - 0.01% (3)	0.01%- 0.1% (4)	0.1%-1% (5)	1%-10% (6)	Over 10% (7)
A. Tiny credit unions							
1. 1990	0.0	0.0	0.6	12.6	72.8	12.6	1.3
2. 2000	0.0	0.0	2.2	33.3	59.8	4.2	0.5
3. 2010	0.0	0.0	4.1	35.6	53.7	5.8	0.8
4. 2017	0.0	0.0	4.8	40.9	50.1	3.6	0.5
B. Smallish credit unions							
5. 1990	0.7	2.2	13.2	48.4	31.0	3.8	0.7
6. 2000	2.5	9.4	36.5	44.9	6.2	0.4	0.1
7. 2010	2.6	6.6	26.2	46.1	16.5	1.8	0.2
8. 2017	3.1	8.6	32.1	50.0	6.0	0.2	0.0
C. Medium credit unions							
9. 1990	4.8	12.1	26.1	33.9	18.0	3.8	1.3
10. 2000	16.1	21.8	30.1	25.3	6.6	0.2	0.0
11. 2010	18.4	23.0	30.3	20.0	6.5	1.6	0.2
12. 2017	11.0	21.5	34.4	24.8	7.6	0.7	0.0
D. Tiny commercial banks							
13. 1990	0.0	0.6	10.8	17.2	58.0	12.1	1.3
14. 2000	0.0	7.1	28.6	30.0	32.6	1.4	0.0
15. 2010	0.0	0.0	5.3	15.8	49.1	29.8	0.0
16. 2017	0.0	6.9	6.9	20.7	58.6	6.9	0.0
E. Smallish commercial banks							
17. 1990	2.4	3.2	12.1	38.8	35.4	5.9	2.2
18. 2000	6.9	7.1	19.5	46.9	19.3	0.4	0.1
19. 2010	5.0	4.5	13.7	37.8	33.7	4.0	1.2
20. 2017	6.3	6.3	27.4	51.1	8.2	0.6	0.1
F. Medium commercial banks							
21. 1990	0.6	1.0	7.6	46.9	38.3	4.4	1.2
22. 2000	1.2	3.0	15.0	55.9	24.6	0.2	0.0
23. 2010	1.1	1.7	9.0	41.1	38.4	5.7	3.0
24. 2017	1.2	3.3	23.5	65.0	6.3	0.5	0.1
G. Large commercial banks							
25. 1990	0.2	2.1	2.6	42.1	46.7	5.2	1.2
26. 2000	1.4	3.7	5.1	59.5	28.7	1.6	0.0
27. 2010	1.4	1.6	3.7	11..4	55.2	19.4	7.3
28. 2017	1.3	1.8	3.8	49.8	42.7	0.5	0.0

Note 1: EPFs below 0.1% (columns 1-4) are commonly deemed “safe” and those above 0.1% (columns 5-7) are commonly deemed “risky.”

Note 2: all boundaries between asset sizes are adjusted for inflation, expressed in 2016 dollars. Tiny institutions have fewer than $10 million (M) in assets, smallish have $10-100M, medium have $100M - $1 billion (B), and large have more than $1B.

Table 8 and Figures 4 through 6 present these distributions for three representative years: 1990 (during the subperiod with many failures associated with the thrift crisis), 2000 (during the earlier subperiod with relatively few failures), 2010 (during the period with many failures associated with the financial crisis), and 2017 (the most recent year). We computed the distribution of estimated probabilities of failure for each year (e.g., 2017) using data for institutions as of December 31 on the previous year (i.e., 2016). These distributions allow us to consider not how many institutions of each type would have failed, but how much, according to our model, different types of institutions were at risk of failure.

In Table 8, the cells in each row present the percentage of institutions with a given EPF (and thus total 100 per row). The four left-most columns present EPFs under 0.1% that are commonly considered “safe” in Basel standards. The three right-most columns present EPFs greater than 0.1%, or risky institutions. For ease of presentation, we placed a solid vertical line between the two sets of safer and riskier institutions. The panels present EPFs for 1990, 2000, 2010, and 2017 for credit unions that were tiny, smallish, and medium, and commercial banks that were tiny, smallish, medium, and large.

Table 8

Distributions of Estimated Probabilities of Failure (EPFs) of Credit Unions and of Commercial Banks, by Size, 1990, 2000, 2010, and 2017

	Under 0.0001% (1)	0.0001% -0.001% (2)	0.001% - 0.01% (3)	0.01%- 0.1% (4)	0.1%-1% (5)	1%-10% (6)	Over 10% (7)
			A. Tiny credit unions				
1. 1990	0.0	0.0	0.6	12.6	72.8	12.6	1.3
2. 2000	0.0	0.0	2.2	33.3	59.8	4.2	0.5
3. 2010	0.0	0.0	4.1	35.6	53.7	5.8	0.8
4. 2017	0.0	0.0	4.8	40.9	50.1	3.6	0.5
			B. Smallish credit unions				
5. 1990	0.7	2.2	13.2	48.4	31.0	3.8	0.7
6. 2000	2.5	9.4	36.5	44.9	6.2	0.4	0.1
7. 2010	2.6	6.6	26.2	46.1	16.5	1.8	0.2
8. 2017	3.1	8.6	32.1	50.0	6.0	0.2	0.0
			C. Medium credit unions				
9. 1990	4.8	12.1	26.1	33.9	18.0	3.8	1.3
10. 2000	16.1	21.8	30.1	25.3	6.6	0.2	0.0
11. 2010	18.4	23.0	30.3	20.0	6.5	1.6	0.2
12. 2017	11.0	21.5	34.4	24.8	7.6	0.7	0.0
			D. Tiny commercial banks				
13. 1990	0.0	0.6	10.8	17.2	58.0	12.1	1.3
14. 2000	0.0	7.1	28.6	30.0	32.6	1.4	0.0
15. 2010	0.0	0.0	5.3	15.8	49.1	29.8	0.0
16. 2017	0.0	6.9	6.9	20.7	58.6	6.9	0.0
			E. Smallish commercial banks				
17. 1990	2.4	3.2	12.1	38.8	35.4	5.9	2.2
18. 2000	6.9	7.1	19.5	46.9	19.3	0.4	0.1
19. 2010	5.0	4.5	13.7	37.8	33.7	4.0	1.2
20. 2017	6.3	6.3	27.4	51.1	8.2	0.6	0.1
			F. Medium commercial banks				
21. 1990	0.6	1.0	7.6	46.9	38.3	4.4	1.2
22. 2000	1.2	3.0	15.0	55.9	24.6	0.2	0.0
23. 2010	1.1	1.7	9.0	41.1	38.4	5.7	3.0
24. 2017	1.2	3.3	23.5	65.0	6.3	0.5	0.1
			G. Large commercial banks				
25. 1990	0.2	2.1	2.6	42.1	46.7	5.2	1.2
26. 2000	1.4	3.7	5.1	59.5	28.7	1.6	0.0
27. 2010	1.4	1.6	3.7	11..4	55.2	19.4	7.3
28. 2017	1.3	1.8	3.8	49.8	42.7	0.5	0.0

Note 1: EPFs below 0.1% (columns 1-4) are commonly deemed "safe" and those above 0.1% (columns 5-7) are commonly deemed "risky."
Note 2: all boundaries between asset sizes are adjusted for inflation, expressed in 2016 dollars. Tiny institutions have fewer than $10 million (M) in assets, smallish have $10-100M, medium have $100M - $1 billion (B), and large have more than $1B.

Figure 4 and Table 8 compare the full EPF distributions of smallish credit unions (from row 7) and of smallish commercial banks in 2010 (from row 19). These distributions provide one example of how, according to our models, for most time periods and most asset sizes, credit unions seem to be less likely to fail (or less risky) than similarly-sized commercial banks. In particular, the figure shows that fewer smallish credit unions (19%) have EPFs that identify them as risky (i.e., larger than 0.1%) than smallish commercial banks (39%).

Figure 4:

Distribution of Estimated Probabilities of Failure (EPFs)

of Smallish Credit Unions and of Smallish Commercial Banks, 2010

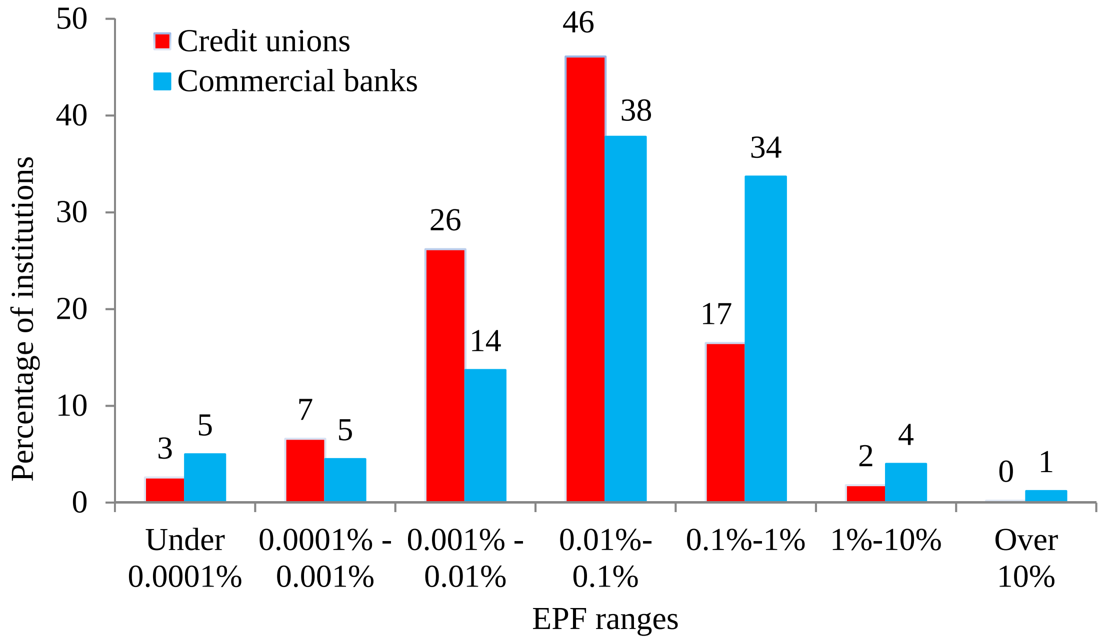
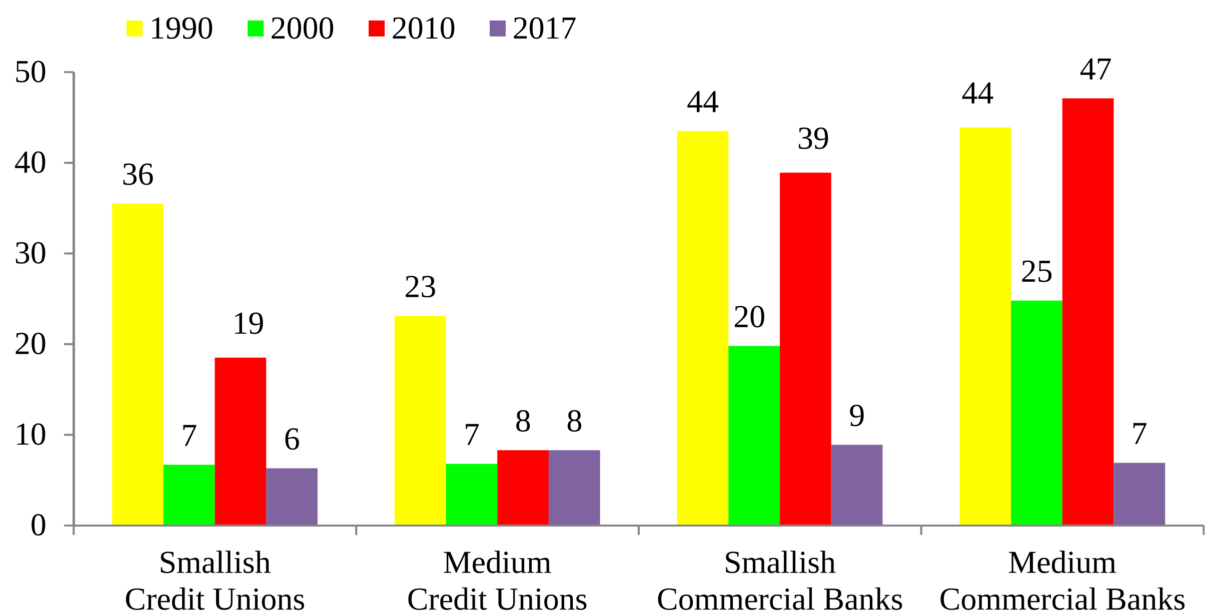


Figure 5 and Table 8 focus on narrower fractions of these distributions (i.e., the rightmost tails of risky institutions) for a larger number of time periods (1990, 2000, 2010, and 2017) for both credit unions and commercial banks. The figure highlights that the fraction of risky institutions (i.e., with high EPFs) were unsurprisingly larger during periods with more failures and smaller during periods with fewer failures. However, we also find that while the share fell markedly from 1990 to 2000 for all four subsets of smallish and medium credit unions and commercial banks, the increases from 2000 to 2010 were much smaller among credit unions than among banks. For instance, the fraction of risky medium credit unions only increased from 7% in 2000 to 8% in 2010, while for medium commercial banks it increased from 25% to 47%.

Figure 5

Percentage of Credit Unions and of Commercial Banks

with EPFs Greater Than 0.1%, by Size, 1990, 2000, and 2010



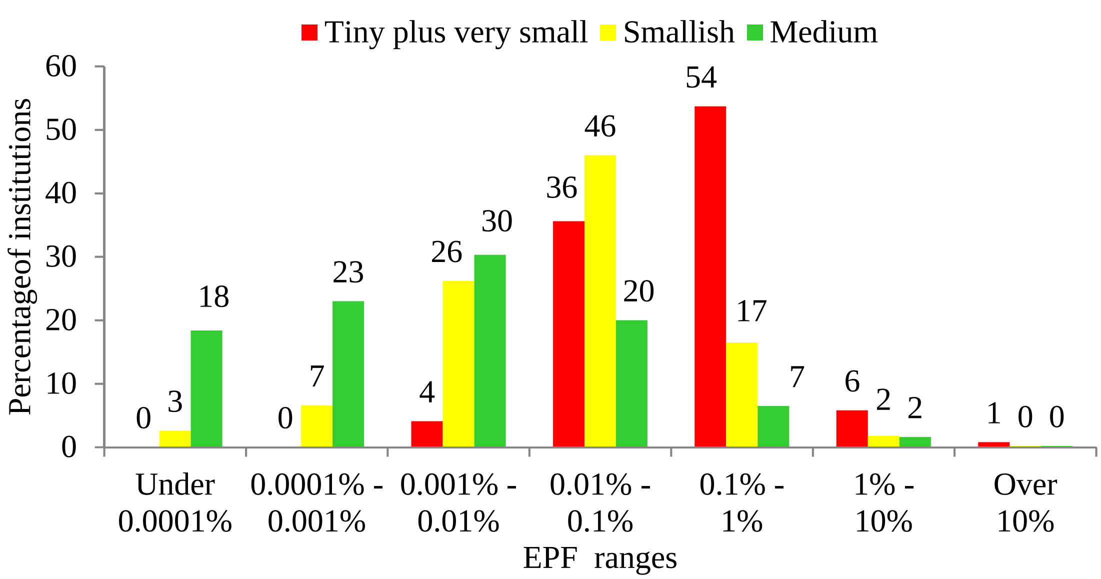
We constructed these EPFs using common sets of coefficients across all time periods so that we could clearly identify shifts in EPFs as resulting from changes in institutions' financial characteristics and in macroeconomic conditions. In section 2, we observed that the increase in credit unions failure rates from the quiescent period to the financial crisis (from 0.18% to 0.27%) was much smaller than that for commercial banks (from 0.05% to 1.02%). Our EPFs, then, would seem to indicate that the smaller increase in credit union failures is largely explained by a smaller degree of change (i.e., deterioration) in their financial characteristics.

Finally, Figure 6 and Table 8 provide some evidence that during the most recent crisis, among credit unions, failures (and in particular the risk of failure) may continue to be strikingly inversely related with asset size. Thus, over half (60%) of tiny credit unions have EPFs above 0.1% and are risky. Among smallish credit unions, risks of failure are substantially lower with about half (46%) of institutions having EPFs in the 0.01-0.1% range, that is on the safer side of the 0.1% boundary. Among medium credit unions, risks of failure are generally very low with roughly one fifth of institutions in each of the four safest EPF ranges (totaling 92% of institutions).

Figure 6

Distributions of Estimated Probabilities of Failure (EPF)

of Tiny, of Smallish, and of Medium-Sized Credit Unions, 2010



8. Summary and implications

Based on our new database of credit union and bank financial conditions and failures, we conducted the first, large-scale, long-term econometric analysis of failures of credit unions. We showed that failure factors had different effects, in size and even in sign, on credit unions than they had on banks. Many variables long been used to predict bank failures also helped predict credit union failures. Failure risks rose at both credit unions and at banks when they had more commercial mortgages, fewer assets, more delinquent loans, less capital, or lower ROAs.

Since the onset of the financial crisis, conditions at credit unions, and especially at banks, deteriorated enough that significant numbers of institutions could have been considered “high risk” and, of course, failures rose considerably after the crisis began.

Interestingly, some failure factors raised risks at banks while lowering them at credit unions. Having more business loans or local unemployment raised bank risks while lowering credit union risks. Presumably factors aggravated diversification risks at banks while reducing them at credit unions. Conversely, having more residential mortgages signaled more failures of credit unions, but not of banks. Recognizing these differences might point to improved regulations about diversification at both banks and credit unions.

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