Failures of Credit Unions and of Commercial Banks:
Similarities, Differences, and Implications

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Abstract

By adding data for 1979-1993, our new dataset enabled the first, large-scale, long-term, econometric analysis of credit union failures. We estimated failure probability models for credit unions and for commercial banks. Several factors affected failure risks of both credit unions and banks. But, credit unions' and banks' failure risks differed importantly due to differences in their asset portfolios and activities and due to differences in how much those factors affected credit unions' and banks' risks. Business loans raised banks', but lowered credit unions', risks. The estimated models point lenders and regulators to risk-preserving trade-offs in micro- and macro-prudential supervision.

1. Introduction

More than 400 banks and more than 100 credit unions failed in the aftermath of the financial crisis and the ensuing Great Recession. Compared with those that failed during the dozen years before the crisis, failures during 2008-2013 both of banks and of credit unions were more numerous, larger, and more costly to their federal insurance funds.

Despite those similarities, there are salient, systematic differences between banks and credit unions. Banks and credit unions generally differ by regulation, history, size, business models, geographic reach, and organizational form.[1] Some of these differences emanate from their different charters; others do not. Regardless, salient, systematic differences across financial institutions can diversify, and thus strengthen, the financial sector. Having financial institutions whose strengths are differentially affected by shocks can make it less likely that the economy will be harmed by reduced efficiency of the financial sector's providing credit and other financial services. In that way, sectoral diversification also provides the protections for the economy that recently-implemented increases in capital requirements seek to provide.

Because they had relatively few assets and had imposed few losses on their insurance fund, credit union failures have rarely been analyzed systematically. More recently, however, credit unions had over $1.2 trillion in assets, had over 100 million members, and losses had imperiled their insurance fund. Thus, the credit union industry has become large enough to consider its potential for diversifying the financial sector.

[1] Perhaps surprisingly, although credit unions' assets have grown somewhat faster than banks, for more than three decades the relative number of credit unions to banks did not change substantially.

In addition to shedding light on the diversification of the financial sector, assessments of credit union failure probabilities, and their sources, may inform those who are more directly affected by actual or prospective failures: uninsured creditors (including uninsured depositors), firms that rate the creditworthiness of depositories, federal deposit insurers (the National Credit Union Administration (NCUA) and the Federal Deposit Insurance Corporation (FDIC)), and taxpayers.

One indicator of the extent of sectoral diversification is how much differently the components of their portfolios (of assets) affected the conditions of credit unions compared the components' effects on the conditions of banks. Another indicator is how much differently local economic conditions affected credit unions compared with how much they affected banks.

To help us assess the effects of their portfolios and of local economic conditions on conditions of each group, we estimated and compared equations for predicting future failures of commercial banks and of credit unions. We used them to analyze how much banks' failure probabilities changed relative to those of credit unions if the two groups made the same portfolio shifts. We also used them to calculate how much each group's failure probabilities rose and fell over time as they shifted portfolios and as local economic conditions changed.

While its relatively small size weakened research interest in the credit union industry in the past, sample size may have also reduced interest until now. Only for the years from 1994 onward were the data for individual, federally-insured credit unions available in a tractable, public database. And, the mostly-tranquil era for credit unions from 1994 until the onset of the financial crisis fueled little research. Nor did failures, which consisted overwhelmingly of small credit unions that imposed even smaller costs on insurance funds, spark lots of research. The resurgence of credit union (and commercial bank) failures after 2007 revived interest in their causes and effects.

To provide the first, large-scale, long-term, econometric analysis of credit union failures, we constructed a new database for credit unions. We unearthed data for individual credit unions that had been collected in the past, but then, in effect, became unavailable and unrecognized due to the advance of technology and retreat of perceived pertinence. Eventually, we obtained and added data for 1979-1993 to our database. The database that we constructed then contains the annual data for financial-statement variables for federally-insured credit unions for 1979-2016. Our database also identifies the credit unions that failed then. Having added data for 1979-1993 enables failure and other analyses of credit unions to include the tumultuous years before 1994, when banks were beset by crises and when credit union failure rates were similar to those of banks.

We used our data to estimate the effects of their own financial conditions on one-year-ahead failure probabilities of banks and of credit unions, while controlling for their local economic conditions. Both banks and credit unions were more likely to fail for several of the same, unsurprising reasons. Both groups failed more when they had more commercial-real-estate loans, more delinquent loans, more noninterest expenses, fewer assets, less capital, and lower earnings.

In contrast, some important factors hurt banks, but helped credit unions, and vice versa. 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. In addition, within credit unions and banks, the size and significance of failure factors sometimes differed by their asset sizes and by time period.

Based on our estimated logits, for each of five size groups, for banks and for credit unions, for individual years, we calculated distributions of failure probabilities. The distributions show how much differences in portfolio shares contributed to cross-sectional distributions and contributed to shifts of distributions over time. We found that, after the depositories' turbulent years in the early-1990s, credit unions' failure probabilities fell much more than those at same-size banks. By the time that the financial crisis and Great Recession arrived, many more banks than credit unions had a one-year-ahead probability of failure (EPF) that exceeded a high-risk threshold of 0.1 percent (10 basis points). For depositories with assets between $100M and $1B, only eight percent of credit unions exceeded the threshold, barely more than in 2000. Over the same time, the high-risk share of banks of that size rose from 25 to 47 percent. Thus, their pre-crisis conditions account for a substantial portion of the burst of bank failures after 2007.

Section 2 reviews research on the failures of commercial banks, mutual and stock thrifts, and credit unions. Section 3 compares failure rates of credit unions to those of banks. Section 4 discusses how we estimated failure probabilities. Section 5 shows estimated logits for failures of credit unions and failures of banks, by asset sizes and for sub-periods of our 1980-2016 sample period. Section 6 displays summary statistics for our failure factors. It also shows distributions of failure probabilities for credit unions and for banks, by asset sizes and by sub-period. Section 7 summarizes our findings and discussions their implications for credit unions, banks, and policymakers.

2. Prior studies of failures

The size of the banking industry, the large and fluctuating numbers of bank failures, and the ready availability of data have generated to a long trail of studies that analyzed bank failures statistically.[2] In addition to academic interest, banks' supervisory agencies have long used statistical methods to gauge risks of bank failures.

Compared with those of banks and of thrifts, failures of credit union have been studied only sporadically and rarely econometrically. Studies of credit union failures that mimicked the statistical methods long applied to bank failures are rare or nonexistent for the same reasons that bank studies are numerous. Only recently had credit unions became a $1 trillion industry, failed credit unions and the losses that they imposed on their insurance fund were small, and data was often not readily available. As a result, so far as we know, ours is the first, large-scale, long-term, econometric analysis of credit union failures. As such, it is also the first study to compare directly the effects of failure predictors for credit unions with those for banks.

The number of studies that focus on failures of depositories ebbs and flows with the numbers and (asset) sizes of failures and with the amounts of the losses that failures impose on federal insurance funds. From the early 1980s through the middle of the 1990s, thousands of banks and thrift institutions failed and imposed losses large enough to render their insurance funds, in effect, insolvent. That experience spawned number studies that sought to identify predictors of failures. In contrast, during the relatively-calm decade before the financial crisis and the Great Recession, both failures and studies of failures were rare.

Statistical studies of bank and thrift failures typically relied on data for financial-statement variables that regulators required. Because relatively few depositories themselves have been publicly traded, their market values were rarely incorporated. Because few of their assets or

[2] Demyanyk and Hasan (2010) argue that advances in data availability and in methods of data analysis, especially the methods more commonly used in operations research, ought to be used to improve predictions of crises and failures.

liabilities were publicly traded or assigned market-mimicking values, data for book values of balance-sheet and income-statement variables are used. While regulators assign categorical values for “management” as part of CAMELS or other ratings of depositories, those values are confidential.

a. Statistical methods and findings

Before there were statistical model of bank failures, Beaver (1966) and Altman (1968) built econometric models on financial ratios to predict bankruptcies (i.e., failures) of nonfinancial firms. Many similar studies followed their lead and applied their approaches to failures of depositories. The Meyer and Pifer (1970) study of commercial banks was among the earliest to study failures of depositories with statistical methods. Similarly, Altman (1977) focused on thrift failures and Kharadia and Collins (1981) focused on credit union failures.

From those beginnings, greater ease and capabilities of computing made it practical to analyze failures with a growing array of statistical methods applied to ever-larger databases of data for individual depositories. Over time, the methods that were used evolved from 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 models (Whalen 1991), trait recognition (Kolari et al. 2001), Markov models (Glennon and Golan 2003), and multinomial logit (Oshinsky and Olin 2005). See Demirguc-Kunt (1989), Altman and Saunders (1998), and King et al. (2006) for surveys of econometric models for predicting failures of depositories.

While different statistical techniques have relative advantages and shortcomings in different settings, the logistic specification (logit) has long been the standard in failure studies

(King et al. 2006). Martin (1977) argued that logit is preferable, for example, to discriminant analysis since logit does not require equal sample sizes for the comparison groups. Since the annual failure rates of depositories have tended to be one-half of one percent or less, logits can be estimated with samples that are vastly larger. Testimony to the dominance of logits in failure studies appears in the routine comparisons to logits by proponents of other methods.

In addition to pioneering the use of logit, Martin (1977) showed the way for ensuing studies. As predictors of failures, he settled on financial ratios that served as measures of capital adequacy, asset quality, earnings, and liquidity. The elements of the primary system used by U.S. banking supervisors to rate banks, the Uniform Financial Rating System or CAMELS, largely mimics the Martin measures. Adopted in 1979, the elements of the rating system initially 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.

Early studies of failures typically used data for small numbers of banks over short periods. Soon thereafter, studies used data for thousands of depositories over lengthening sample periods. Martin (1977) ushered in the large-sample era when he used 30,000 observations for the individual institutions that the Federal Reserve supervised over seven years. In the aftermath of the banking and thrift crises then ended in the early 1990s, Harrison and Ragas (1995) and Fuller and Kohers (1994) used data for thrifts during 1980-1989 and during 1983-1991. Similarly, Jordan and Rosengren (2002) used data for banks during 1985-2001 and Oshinsky and Olin (2004) used data for banks during 1990-2002.

The Martin approach has proven reliable, in the sense that most follow-on studies of U.S. commercial bank failures included variables as measures of CAMEL elements, drew data from Call Reports, and generally found them to be statistically significant (King et al. 2006). More recently, Cole and White (2015) concluded that bank failures during 2009 were largely attributable to the same, CAMEL-inspired factors that led to failures during banking-crisis years of 1985-1992. Thus, the specifications of recently-estimated models for predicting bank failures fit comfortably within the range of models developed over the past four decades.

Banking supervisors validated applying statistical methods to financial ratios when they built early warning systems (EWS) solely on objective data, such as those in Call Reports, for bank failures. These off-site systems were designed to supplement the information gleaned from on-site bank examinations (Kolari et al. 2001 and Jordan and Rosengren 2002). King et al. (2006) reviewed 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), which the OCC adopted in 1975. Due to computational constraints, the NBSS asked supervisors to rank banks by their financial ratios in order to detect outliers within peer groups. In 1977, the Federal Reserve launched the Minimum Bank Surveillance System (MBSS), which was the first econometric model used by bank supervisors for off-site surveillance (Korobow, Stuhr, and Martin 1977). Since 1993, the Federal Reserve has used logits to estimate its System to Estimate Examination Ratings (SEER) for predicting failure probabilities (King et al. 2006).

The size distribution of U.S. commercial banks has long had a low mean, high variance, and a skew to the right. The assets of a few dozen of the largest U.S. commercial banks total more than the assets of the remaining 5000+ banks. Banks tend to differ by size in several ways. Among the ways they do (or may) differ are in their product offerings, sizes of market served, regulations, access to capital markets, and average costs (due to any economies of scale). The largest of the very large banks have also been “too big to fail.” The small numbers of the very largest banks, their many fewer economic insolvencies, and their vastly-fewer-yet declared failures argue for analyzing them separately. It is more clear that there are size-related differences in banks and in credit unions than it is that the differences would translate into failure models that differ by size is much less clear, and much less documented.

Demirguc-Kunt (1989) and Kolari et al. (2001) are among the few studies to report failure models for different bank sizes. Less directly, size-related effects are incorporated in many studies either by using a sample restricted to banks with assets within a specified range or by including asset size as a failure factor, or both. We do both, and also show estimates for separate size-based samples.

Failure studies have sometimes included state (or, local) or national economic variables alongside banks' financial variables. The evidence that economic variables help predict failures is mixed. For example, Glennon and Golan (2003) detected significant effects, while Nuxoll (2003) concluded that macroeconomic variables failed to improve failure predictions. Aubuchon and Wheelock (2010) concluded that local economic conditions did contribute to bank failures during 2007-2010. Regarding the usefulness of macroeconomic forecasts for predicting bank failures, Jordan and Rosengren (2002) reported mixed results: In the presence of controls for bank-specific financial variables, macroeconomic forecasts helped during troubled years, but not during prosperous years.

Failures do not always conjure up the Cole and White (2015) sense of *déjà vu*. While failure factors have been quite reliably identified through the years, their estimated effects, as well as the statistical significance, of failure factors have varied somewhat over time. Fuller and Kohers (1994), Harrison and Ragas (1995), and Helwege (1996) compared models for predicting thrift failures that were estimated over different years. King et al. (2006) compared the characteristics of failing and surviving commercial banks during 1984-94 with those during

1995-2003. Each found that little change over time in which factors predicted failures, but also found that the estimated effects of the factors sometimes differed greatly over time. King et al. (2006) reported that the estimated effects on failure probabilities and statistical significance of asset size and of commercial real estate mortgages declined importantly by the late 1990s.

For the reasons we gave above, credit union failures have not been studied often or intensively. After the flood of failures through the mid-1990s, interest in credit union failures picked up a little. Gordon, et al. (1987), Gordon (1991), and Shafroth (1997) identified riskier assets and higher noninterest expenses as factors that likely contributed to failures of credit unions and to the losses that failures imposed on the federal (share) insurance fund. And, even before those studies, Kharadia and Collins (1981) estimated linear probability models for failures of federal credit unions during 1960-71, before the advent of federal share insurance. Kane and Hendershott (1996) used logits to model failures of federally-insured credit unions during 1987-1990.

b. Mutual and stock ownership

Bank and credit union portfolios differ by asset category. For example, banks have more business-related loans and fewer consumer-related loans. Those differences affect failure probabilities. Apart from those effects, we seek evidence about how differently bank and credit union failure probabilities are affected the same portfolio shift, say moving one percent of assets out of residential and into commercial mortgages.

Another difference is that all commercial banks are stock-owned and all credit unions are mutually-owned. Thus, differences between banks and credit unions inevitably incorporate whatever repercussions emanate from their form of ownership. It may be that ownership affects asset shares. Ownership may also affect how much the assets within an asset category affect failure probabilities. That is, ownership might affect the value of the regressor or the value of its coefficient, or both. Regardless, ownership is likely to affect probabilities and estimates of failure models to unknown extents. For some insight into the incentives and effects of ownership form, we can look to thrifts, which may be either stock- or mutually-owned. (Their form of ownership does not materially affect their regulation or other constraints.)

Mutuals are often thought to be better than stock companies at solving agency conflicts between customers and owners (because customers are the owners), but worse at solving manager-owner conflicts (because of the absence of a market for control). Rasmusen (1988) notes that mutuals tend to have weaker governance and performance incentives (partly due to the absence of stock). As a result, mutual managers may incur excessive costs and to take too few risks. Harris and Raviv (1991) describe the stronger incentives for stock owners to substitute toward riskier assets, at the expense of (uninsured) creditors.

Evidence from mutual and stock thrifts tends to suggest that mutuals have been less cost-conscious and less willing to take risks. Vergrubbe and Jahera (1981), Akella and Greenbaum (1988), and Sfiridis and Daniels (2004) found that mutual were less efficient than stock thrifts. Hermalin and Wallace (1994) concluded that stock thrifts were more efficient and that they took more risks within asset categories. Esty (1997) found that the profits of stock thrifts were more volatile, suggesting that they took more risk. He also found that converting to stock ownership was followed by thrifts' having riskier assets and more volatile profits. On the other hand, Cebenoyan, et al. (1993a, 1993b) detected no difference in efficiency associated with form of thrift ownership.

3. Data for Failures and Insurance-Fund Losses

We obtained aggregate and individual data for failures of credit unions from the NCUA and failures of commercial banks for 1971-2016 from the FDIC (2017). [3] We obtained (end-of-year) Call Report data for 1979-2016 for credit unions from the NCUA (2017) and for commercial banks from the Federal Reserve Bank of Chicago (FRB Chicago 2017) and the Federal Financial Institution Examination Council (FFIEC 2017).[4]

Table 1 shows annual failure rates in percent, the numbers of failures, and the numbers of credit unions and of commercial banks for selected years and asset-size ranges.[5] Table 1 distinguishes two sub-periods when failure rates were higher (1980-1993 and 2008-2013) and two sub-periods when failure rates were lower (1994-2007 and 2014-2016).[6] To calculate average failure rates for each sub-period, we first computed annual failure rates (i.e., the number of failures during a year relative to the number of institutions as of the previous December 31). Table 1 then shows the average of each period's annual failure rates. Table 1 also distinguishes (asset) size categories for credit unions and for banks: Institutions under $10M of assets are tiny; those with between $10M and $100M are smallish; those with between $100M and $1B are

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3. Data were available for all insured credit union failures starting in 1971, but were only available by size from 1981 onward.
4. For simplicity, we use the term credit union to refer only to natural-person, federally-insured credit unions. We excluded credit unions that were either uninsured or insured by non-federal entities, such as states. Thus, our data, including asset totals and numbers of credit unions, include only federally-insured credit unions. The National Credit Union Share Insurance Fund (NCUSIF), which provides federal share (or, deposit) insurance for federally-chartered and state-chartered credit unions, began in 1971. We included natural-person credit unions, which serve individuals, but excluded corporate credit unions, which only serve other credit unions.
5. 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.
6. We further separated 1980-1993 into 1980-1986 and 1987-1993, because credit unions and commercial banks began to report many more variables after 1986, some of which we used for our latter-period estimates in Tables 2-5. The specifications in Table 6 that used pre-1986 data could not include the extra variables.

medium; and those with over $1B are large. Boundaries between size groups were constant in 2016 dollars.[7]

Table 1

Failures and Numbers of Credit Unions and Commercial Banks, by Size and by Years

	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 (percent)					
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: Boundaries between asset-size groups were set in 2016 dollars. Tiny institutions had fewer than $10 million (M), smallish had $10-100M, medium had $100M - $1 billion (B), and large had more than $1B in assets. Failure rates for multi-year periods were averages of annual failure rates.

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

Both credit unions and banks failed at very high rates in the earlier years of our sample (1987-1993). Many fewer then failed during the quiescent years of 1994-2007. After that, the financial crisis and the Great Recession and their attendant mortgage and housing woes boosted

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

failure rates, especially for banks. Though their timing was not always the same, over the 1980-2016 period failures of credit unions were about the same number as of banks and their overall failure rates were remarkably similar (0.44 percent and 0.48 percent).

Until the most recent spate of failures, smaller institutions typically failed at higher rates than larger ones. We see that pattern for both credit unions and banks in panel A of Table 1. We also see that, in the aftermath of the financial crisis and the Great Recession, the pattern shifted toward higher failure rates at larger credit unions and banks.

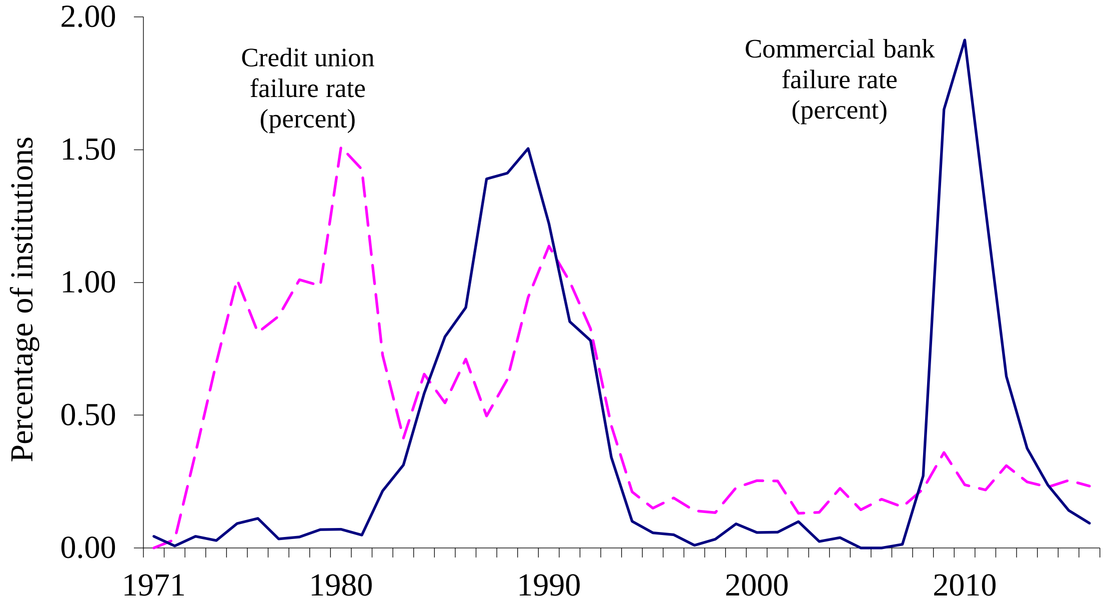
Comparing institutions of the same size highlights a difference that aggregate ratios do not: credit unions generally had lower failure rates than commercial banks of the same sizes. The average annual failure rates over 1890-2016 for tiny credit unions and tiny banks were 0.62 and 0.68 percent; for large credit unions and large banks the failure rates were 0.02 and 0.53 percent, and so on. Differences in the timing of failures and in same-size failure rates suggest that credit unions may have differed enough from banks to add meaningful, though hardly complete, diversification to the financial sector.

Panel C of Table 1 shows the numbers of credit unions and of banks in operation at the ends of selected years. Despite all of the differences and changes in their business models and regulations, the total number of credit unions mirrored that of banks, especially since the mid-1980s. Both saw their numbers cut by two-thirds over 1979-2016. Of those declines, it was the tiny and smallish credit unions and banks where exits were concentrated. At the same time, the distributions of sizes of credit unions differed noticeably from those of banks over these years: There were very few large credit unions and there were very few tiny banks. Therefore, we estimated failure equations both over aggregate samples and over size-based samples.

Figures 1-3 depict the extent of failures and of costs to their insurance funds for credit unions and for banks. Figure 1 shows the annual failure rates for all credit unions and for all banks for 1971-2016. Very shortly after the NCUSIF began insuring balances in share accounts, credit union failure rates soared, and then stayed high for a decade. In contrast, failure rates for banks remained low through the early 1980s.

Figure 1

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



Sources: Wilcox (2005), NCUA (2017), FDIC (2017), FRB Chicago (2017), FFIEC (2017).

Presumably, the new rules and regulations that accompanied share insurance effectively forced out credit unions deemed too weak to continue operations. These failures recall that thousands of banks never reopened after the bank holidays of 1933. Those failures, just before the formation of the FDIC, contributed considerably to the low bank failure rates during the early years of the FDIC.

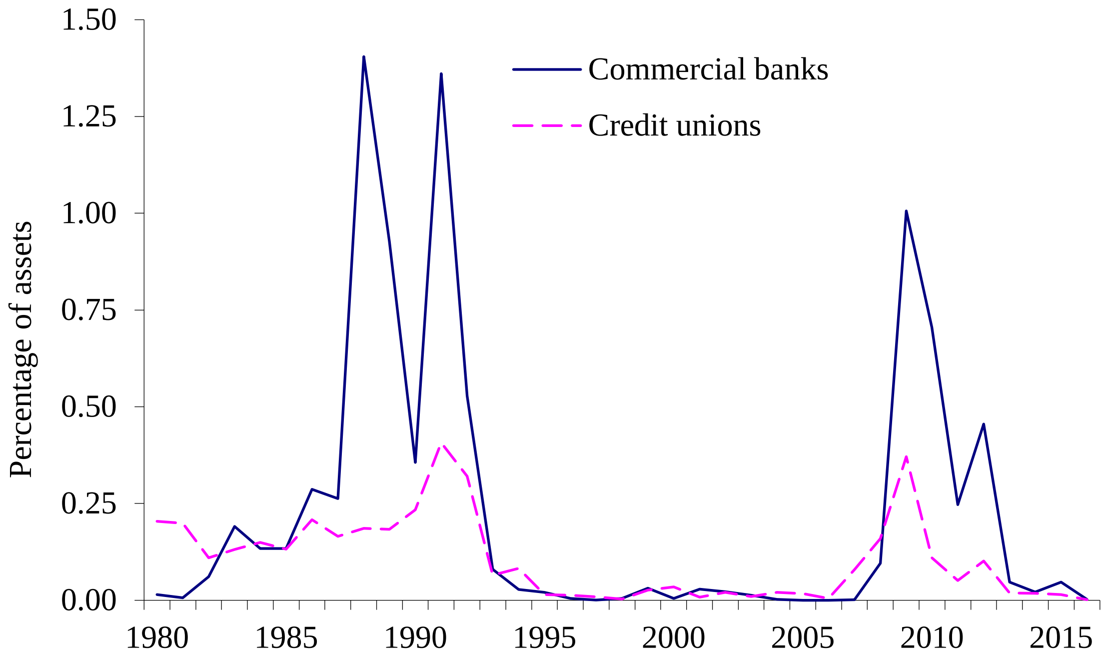
From the early 1980s onward, Figure 1 shows that credit union and bank failure rates showed some tendency to rise and fall together. But, their swings generally differed in amplitude and their timing reflected industry-specific problems. The solid line shows that the bank failure rate was much more volatile over time. Over a few years, the bank rate could rise from nearly zero to about 1.50 percent, and then fall by the same amount. After the restructuring of the credit union industry through the 1970s, only around 1990 did credit union failure rates reach one percent. Starting in the mid-1980s, credit unions and banks failed for different reasons. The tidal wave of bank failures then stemmed from problems with commercial real estate loans in particular, and to some extent from other business loans. Credit unions had very few loans of either category. Later, the 1990-1991 recession led to significant losses on consumer loans, which dominated credit union portfolios.

Table 1 showed that banks generally have been quite a bit larger than credit unions. It also showed that, after 2007, failure rates for larger banks and credit unions were no longer lower than for their smaller brethren. Figure 2 incorporates these differences by showing the percent of bank and of credit union assets (as of the end of the prior calendar year) that were held by each year's failed institutions. Put another way, it shows asset-weighted failure rates. Because many more relatively-large banks failed, this failure rate for banks averaged double that for credit unions. And, the peaks in banks' failure rates were more than double those of credit unions.[8]

8. Data for the assets of individual institutions that failed is available for years starting with 1980. Note that Figure 1 started with data for 1971.

Figure 2

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

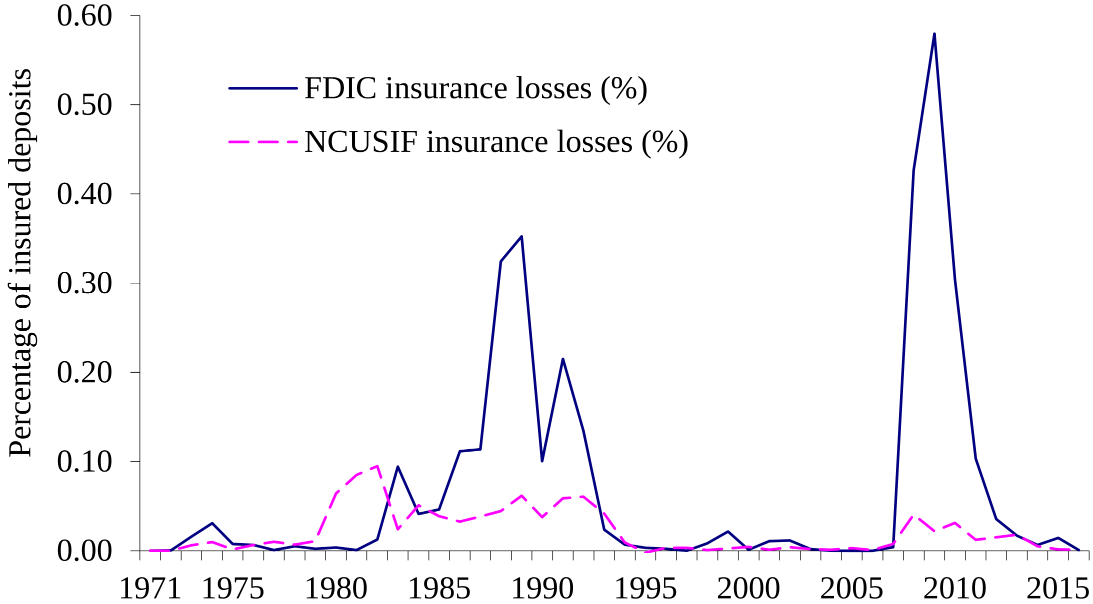


Sources: NCUA (2017), FDIC (2017), FRB Chicago (2017), FFIEC (2017).

Figure 3 shows how expensive failures were to the federal insurance funds for shares and deposits. The solid line plots the annual losses incurred by the FDIC per insured deposits during 1971-2016; the dashed line plots the loss rate for the National Credit Union Share Insurance Fund (NCUSIF). While the high costs of bank failures starting in the mid-1980s arose from the multitude of smaller failures, the high costs to the FDIC after 2007 arose from many-fewer, much-larger, much-more-expensive failures.

Figure 3

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



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

As hinted by Figure 2, the costs of failures have been much larger to the FDIC, both in dollars and per insured deposits.[9] During 1971-2016, annual FDIC losses per insured deposits averaged 0.07 percent. They peaked at 0.58 percent in 2009. Losses incurred by the NCUSIF were much lower. Annual NCUSIF losses per insured deposits averaged 0.02 percent. They peaked at 0.09 percent in 1982.

Thus, there have large enough differences between banks and credit unions to produce important differences in the extent and in the timing of their failures and of the losses they imposed. The resulting differences in the extent of their troubles provides a route to better overall performance of the financial sector.

9. Wilcox (2005) reported that insurance losses per failing institutions' assets were higher for banks than for credit unions.

4. Specification and Estimation

We next set out to identify factors that significantly predicted failures of banks and of credit unions. We sought estimates that would provide statistical measures of how similarly and how differently credit unions' and banks' probabilities of failure were predicted by measurable variables.

To do so, we used a panel of annual data for individual credit unions and commercial banks during 1980-2016. This long and wide panel allows us to average effects observed over long time spans, and over both credit unions and banks, or one or the other group. The panel also allows us to split our data by time and by institutions' characteristics, such as size, portfolio composition, source of revenues, and so on.

We used logits to estimate our failure prediction equations.[10] We set the failure variable equal to one for that calendar year if an institution failed; it was zero otherwise. Of course, most never failed during our sample period. For our right-hand-side variables, we used prior-year data. For financial variables for individual credit unions and banks, we used data as of December 31 of the previous year.[11] For their flows, such expenses or revenues, we used annual data for the previous year. For external variables, such as local unemployment rates, we also used annual data from the prior year.

As we considered candidates for failure factors, we were guided by prior studies and by the availability of variables that were measured quite similarly for credit unions and commercial

10. 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.
11. Rather than drop observations that had extreme outliers, we used histograms for each variable to guide how we winsorized each variable. For example, we changed extreme values for ROA (outside the range from -15 percent to +15 percent) to those endpoints.

banks. We also wanted variables that were available for virtually all credit unions and banks for many years. We present estimates both for an “extended” model, which had a more variables but covered fewer years (i.e., 1987-2016) and a “baseline” model, which had a fewer variables but covered more years (i.e., 1980-2016).

The baseline model included the (ratios to total assets of the amounts of the) following independent variables: (1) asset size (expressed in 2016 dollars, then logged) to control for size-related patterns in failures, (2) securities (plus, for credit unions, other non-cash investments such as deposits in corporate credit unions), (3) residential mortgages,[12] (4) loans other than residential mortgages, (5) total assets minus securities, residential mortgages, loans other than residential mortgages, and cash, (6) provisions for loan and lease losses, (7) capital (net worth for credit unions and equity for commercial banks) per total assets, (8) net income per assets (ROA), and (9) the unemployment rate during the prior year in the state that the institution was headquartered.[13] Throughout, the omitted asset category was cash, which was defined as the sum of cash plus balances due from depository institutions.

The extended model dropped the variable “loans other than residential mortgages” and replaced it with its component variables, which became available starting in 1987. Thus, we added these variables: (10) non-mortgage consumer loans,[14] (11) commercial and industrial

12. In 1986, individual credit unions first reported residential real estate loans other than first mortgages. We estimated total residential mortgages (i.e., firsts plus others) before 1986 by scaling up the amounts of first mortgages that they reported by the national ratio in 1986 of total to first mortgages.
13. 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.
14. 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.

(C&I) loans, (12) commercial mortgages.[15] We also added (13) noninterest expense. The extended model also replaced provisions for loan and lease losses with (14) delinquent loans.[16]

The tables below show estimated logits for samples of credit unions, of commercial banks, and of both. We used Chow tests to determine whether credit union failure probabilities responded differently than banks did. When we rejected the hypothesis of no difference, we then added interaction terms (i.e., the product of each variable and a credit union dummy variable) when we estimated logits with the full sample to see which individual variables had significantly different effects on credit unions and banks.

We then used our logit estimates to calculate distributions of failure probabilities, separately for credit unions and for banks. Apart from how many failed at any time, the estimated distributions show how many institutions could have been considered to be at "high risk" of failing. We also show how the risk distributions changed through time.

5. Estimated Failure Models, by Charter, by Asset Size and by Sub-period

Tables 2 through 6 contain logit estimates of our failure prediction equations. Tables 2-5 show estimates of our extended model for failures by charter (credit union or commercial bank), by asset size, and by sub-period. Table 6 shows results for our baseline model, which has fewer variables over more years than the extended model, by charter and by sub-period.

Column 1 of Table 2 presents results for a sample that included both credit unions and commercial banks. Our results are consistent with the thrust of prior studies. At the one percent

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15. 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.
16. Delinquent loans and noninterest expenses were first reported by commercial banks in 1984.

level, these factors predicted more failures: fewer securities, more commercial mortgages, more C&I loans, smaller asset size, more noninterest expense, more delinquent loans, lower capital, lower ROA, and higher local (i.e., state-level) unemployment rates. The only variables in the extended model that were not statistically significantly associated with failure during the next calendar year were consumer loans and residential mortgages.

We then tested the hypothesis that the extended-model coefficients were the same for credit unions as they were for commercial banks. Because a Chow test decisively rejected that hypothesis, we estimated separate coefficients for credit unions (column 2) and for commercial banks (column 3). In addition, we used the combined sample to estimate how much differently each factor affected credit unions and banks. To do so, for each factor we added a variable that interacted the factor with a dummy variable that was set equal to one for credit unions and zero for banks. Column 4 shows the estimated difference and associated t-test for each factor.

Table 2:

Determinants of Failures of Credit Unions and of Commercial Banks, 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(assets (2016$))	-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 (percent)	0.42	0.36	0.52	
17. R^2	0.20	0.12	0.32	

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

By and large, columns 2 and 3 show that most factors significantly predicted failures of both credit unions and banks in the same direction. For both, these factors raised failure probabilities: fewer securities, more commercial mortgages, smaller size, higher noninterest expenses, more delinquent loans, lower capital, and lower ROAs. And, like the combined sample, neither the sample of credit unions nor the sample of banks produced reliable effects of consumer loans on failures over the entire 1987-2016 period.

Perhaps more interesting were the differences in effects on failures between credit unions and banks in statistical significance, in size, and in sign. Column 4 shows that nine of the 12 factors affected credit union failures by significantly different amounts than they affected (the log odds ratio of) bank failures. For example, having more mortgages, residential or commercial, raised failure probabilities more at credit unions than at banks. So, too, did having larger noninterest expenses, a result that probably reflects banks' being more likely to incur higher costs in connection with higher-revenue activities. Having more capital reduced banks' failure probabilities more, a difference that likely stemmed from banks' generally having had riskier assets.

Columns 2 and 3 show that some factors affected credit union and bank failures in opposite directions. There we see that having more residential mortgages was associated with higher probabilities of failure for credit unions, but lower probabilities for banks. Conversely, increasing C&I lending raised banks' probabilities, but lowered them (albeit insignificantly) for credit unions. We also found that higher state-level unemployment rates raised the risk of bank failures, but had no significant effect on credit unions' risk.

The differences between credit unions and banks in the sizes and signs of these effects help diversify the financial sector. Having a sizeable group of lenders that are relatively unscathed in the face of problems, say in the form of higher unemployment rates, ought to temper declines in the total supply of credit from these lenders. The differences may also point to risk-reducing benefits of further diversification within credit unions and within banks. Our estimates imply that shifting credit unions' assets away from residential mortgages and toward C&I loans might reduce their failure probabilities; shifts in the opposite direction might reduce banks' failure probabilities.

Table 3 shows how estimates vary across size groups. We grouped credit unions and banks by assets: tiny (with under $10M in assets), smallish ($10M-$100M), medium ($100M-$1B), and large (over $1B). Dollar boundaries were adjusted so that size ranges were constant over time in 2016 dollars. To facilitate comparisons across charters, we chose these boundaries in light of the size distributions of credit unions and of banks. We wanted two size groups that each had very many credit unions and very many banks: smallish and medium. In contrast, the tiny group included thousands of credit unions, but relatively few commercial banks. And, the large group included many commercial banks, but only recently included any credit unions. Indeed, since only one large credit union failed during 1987-2016, there are no results to report in column 4.

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(assets (2016$))	-0.10***	-0.56***	-0.28***		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. Number of failures	949	182	37	1	18	760	592	109
16. Failure rate (percent)	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: Boundaries between asset sizes were expressed in 2016 dollars. Tiny institutions had fewer than $10 million (M) in assets, smallish had $10-100M, medium had $100M - $1 billion (B), and large had more than $1B. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level.

Many of the size-based estimates in Table 3 echo the results for all sizes in Table 2. To wit, more failures were predicted by more delinquent loans, lower capital, and lower ROAs, for each size group of credit unions and of banks. And, the differences in sizes and signs between the credit union and bank coefficients in Table 2 generally fit with the estimates in Table 3, though often with much less statistical significance. A notable difference in that regard was that the extent of residential mortgage holdings, while carrying the same signs as in Table 2, no longer significantly affected the failure probabilities of either credit unions or banks. Consistent with the suggestion we made above about banks' noninterest expenses, row 9 in Table 3 shows that higher costs raised failure probabilities for tiny and smallish banks, but lowered them significantly for medium-sized banks and insignificantly for large banks.

Changes, if any, in the economic and statistical significance of failure factors may be permanent or temporary, gradual or sudden. Changes may reflect enduring shifts in the financial sector. Or, they may reflect an unusual circumstance, such as a financial crisis or an epic decline in house prices. To see if estimates based on quiescent periods differed from those based on turbulent periods for lenders, we split our sample into two periods that had more failures (1987-1993 and 2008-2013) and two periods that had fewer failures (1994-2007 and 2014-2016).

Table 4 shows estimates for those four periods. Some effects prevailed through time. For example, having more delinquent loans or having less capital raised failure probabilities for credit unions and for banks in each period. And, having more securities usually reduced failure probabilities, but apparently not during 2014-2016.

Table 4

Determinants of Failures of Credit Unions and of Commercial Banks, by Time Period, 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(assets (2016$))	-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. Number of failures	741	264	119	45	979	58	418	27
16. Failure rate (percent)	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: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level.

Nonetheless, the sizes of estimated effects were far from constant for the samples in Table 4. We documented earlier the large increases over 1979-2016 in the relative sizes and numbers of larger credit unions and banks. One hypothesis, then, is that continual shifts toward larger shares of larger credit unions and banks were an important source of variations over time in individual factors' effects.

Table 4 does not obviously support that hypothesis. Individual factors' effects there did not appear to proceed in one direction. Instead, the effects of failure factors, there seemed more often to be fleeting than constant or unidirectional. For example, in the two periods of high failure rates, residential mortgages first raised credit unions' failure probabilities, but later lowered them. Though too imprecisely estimated to conclude much, if anything, the effects of residential mortgages were larger in the later than in the earlier quiescent period.

A better interpretation is that the estimated effects in Table 4 were episodic. Rather than reflecting continuing shifts of any kind in the credit union and bank industries, the estimated effects of both commercial mortgages and of C&I loans seemed to reflect particular conditions in each period, or episode,. Thus, we found larger effects of these loans on failures during periods when troubles were widespread in their industries. To the extent estimates based on sub-periods, in effect, reflect particular rather than general effects on failures, they are less useful guides for assessing upcoming risks. Thus, unless failure probabilities are conditioned on particular future conditions, probabilities based on longer-sample estimates are likely preferable.

To reduce influences of shifting size shares, Table 5 also shows estimates across time periods, but just for (smallish) credit unions and banks that had $10-100 million of assets. The smallish group had enough credit unions, banks, and failures of each that it provided us with useful samples for our four time periods. As usual, probabilities of failure were higher when credit unions or banks had more delinquent loans, less capital, or lower ROA.

The time patterns of estimates in Table 5 generally conformed to those we saw for all sizes of credit unions and banks in Table 4. In that regard, Table 5 supports the episodic rather than the continuing-shift hypothesis. For both all sizes and for smallish credit unions and banks, we prefer the conclusion that variations in effects over time reflected the particulars of each episode, rather than continuing shifts of asset sizes or of other industry conditions.

Table 6 is based on data for 1980-2016. The benefit of adding 1980-1986 to our estimation sample is that those seven years had high failure rates both for credit unions and for banks. The cost is that credit union data were not available before 1987 for some of the failure factors in Tables 2-5. For credit unions, columns 1 shows estimates for 1980-2016. Empty rows in column 1 indicate that we did not have data before 1987 for consumer loans, commercial mortgages, or C&I loans. Instead, credit unions reported data for their sum as non-residential loans.

Nor did we have data for noninterest expense or for delinquent loans then. In the absence of delinquent loans, we included loan loss provisions as a failure factor. Column 2 shows estimates based only on the seven additional years of 1980-1986. Column 3 used the shorter 1987-2016 period. For comparison, column 4 replicated the results for 1987-2016 that appeared in column 2 of Table 2. Columns 5-8 shows estimates for banks that were based on the same specifications with the same estimation samples that were used for columns 1-4.

The primary implication of Table 6 is that estimated effects were affected much more by adding failure factors than by adding years. Given the same failure factors, the estimated effects in column 1 for 1980-2016 generally differed inconsequentially from the effects for the shorter, 1987-2016 period (column 3). Given the same 1987-2016 sample for credit unions, compared with column 4, the specification in column 3 differs most importantly by including neither noninterest expenses nor delinquent loans, both of which were hugely significant in column 4. The net effect of those forced omissions was that securities lost their significant negative effect and the positive effects of residential mortgages on failures became much large and more significant. In contrast, with the exception of securities at credit unions and residential mortgages at banks, assessments of failure factors would not be much affected by removing 1980-1986 from the estimation period.

Table 5

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

	Smallish Credit Unions				Smallish 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	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(assets (2016$))	-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. Number of failures	114	31	31	6	636	30	78	16
16. Failure rate (percent)	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: Smallish institutions had assets of $10-100M in 2016 dollars. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level.

Table 6:

Determinants of Failures of Credit Unions and Commercial Banks,

By Time Period, 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(assets (2016$))	-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. Number of failures	2,165	996	1,169	1,169	1,904	422	1,482	1,482
16. Failure rate (percent)	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: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level.

6. Estimated Probabilities of Failure

In this section, we show distributions of estimated probabilities of failure (EPFs) for selected years for credit unions and for banks, by size. We calculated EPFs with the logistic estimates in Tables 2-6 and data for individual credit unions and banks. Table 7 shows averages of the failure factors. For convenience, panel A repeats the numbers of credit unions and banks by size by year. Panel B shows asset totals in dollars; Panel C shows each size group's share of industry assets. The remaining panels show averages of annual group-wide ratios to assets.

Table 7 shows that credit unions have been small but growing relative to banks for many years. By 2016, credit union assets totaled about eight percent banks' assets. Table 7 reiterates that the centers of gravity have moved toward larger credit unions and larger banks. Because EPFs vary by size, size shifts translate into shifts of EPF distributions.

Table 7 also shows that, compared with credit unions, banks devoted far more of their assets to commercial mortgages and C&I loans. After all, they are *commercial* banks. While these two loan categories were about five percent of credit union assets during 2014-2016, they were more than 20 percent of bank assets then. Credit unions devoted far more of their assets to household-related loans. These differences in assets and the associated differences in their effects on failures importantly affect EPF distributions.

Table 7

Credit Unions and Commercial Banks, by Size, by Time Period, 1979-2016

	Credit Unions					Commercial Banks				
	All	Tiny	Smallish	Medium	Large	All	Tiny	Smallish	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(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. Assets (percent of industry assets)										
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 (average percent of assets)										
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 (average percent of assets)										
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 (average percent of assets)										
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 (average percent of assets)										
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)

	Credit Unions					Commercial Banks				
	All	Tiny	Smallish	Medium	Large	All	Tiny	Smallish	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	H. Commercial Mortgages (average percent of assets)									
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 (average percent of assets)									
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 (average percent of assets)									
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 (average percent of assets)									
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, average percent of assets)									
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 (average ratio of net income to assets)									
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.

Table 8 and Figures 4 through 6 present distributions of EPFs for selected years: 1990 (when the banking industry was troubled), 2000 (when there were relatively few failures), 2010 (when the financial crisis led to many failures), and 2017 (the most recent year). For each year, we based EPFs on data for the prior calendar year. We used the estimates for credit unions and for banks by size that are shown in Table 3. Those unchanging estimates highlighted the repercussions on EPFs of changes at credit unions and banks over the years.

The rows in Table 8 show the percent of credit unions or banks that had EPFs within the ranges shown at the top of Table 8. For convenience, we refer to EPFs below 0.10 percent (1/1000) as “safe.” We refer to credit unions or banks that had EPFs above 0.10 percent as “risky.” The vertical line in Table 8 reflects that dividing line. For perspective, default probabilities for nonfinancial firms of 0.10 percent, roughly, correspond to a single-A bond rating.

Table 8

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

	Under 0.0001 percent (1)	0.0001 percent - 0.001 percent (2)	0.001 percent - 0.01 percent (3)	0.01 percent- 0.1 percent (4)	0.1 percent-1 percent (5)	1 percent- 10 percent (6)	Over 10 percent (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: EPFs below 0.1 percent (columns 1-4) are commonly deemed "safe" and those above 0.1 percent (columns 5-7) are commonly deemed "risky." Boundaries between asset sizes were 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 displays the EPF distributions for smallish ($10-100M in assets) credit unions and banks shown in Table 8 in a more digestible format. (Percents shown above bars were rounded to integers in the EPF figures.) The red bars in Figure 4 tell us that a great majority of smallish credit unions were “safe” during 2010: 82 percent had EPFs below 0.10 percent. Banks were riskier then, as they usually were. While sixty-two percent of banks were safe, 39 percent were risky, about twice the percentage of credit unions that were risky. Figure 4 was emblematic of the differences between credit union and bank EPFs. For most years and for most sizes, banks tended to have higher EPFs.

Figure 4:

Distributions of Estimated Probabilities of Failure (EPFs)

of Smallish Credit Unions and Commercial Banks, 2010

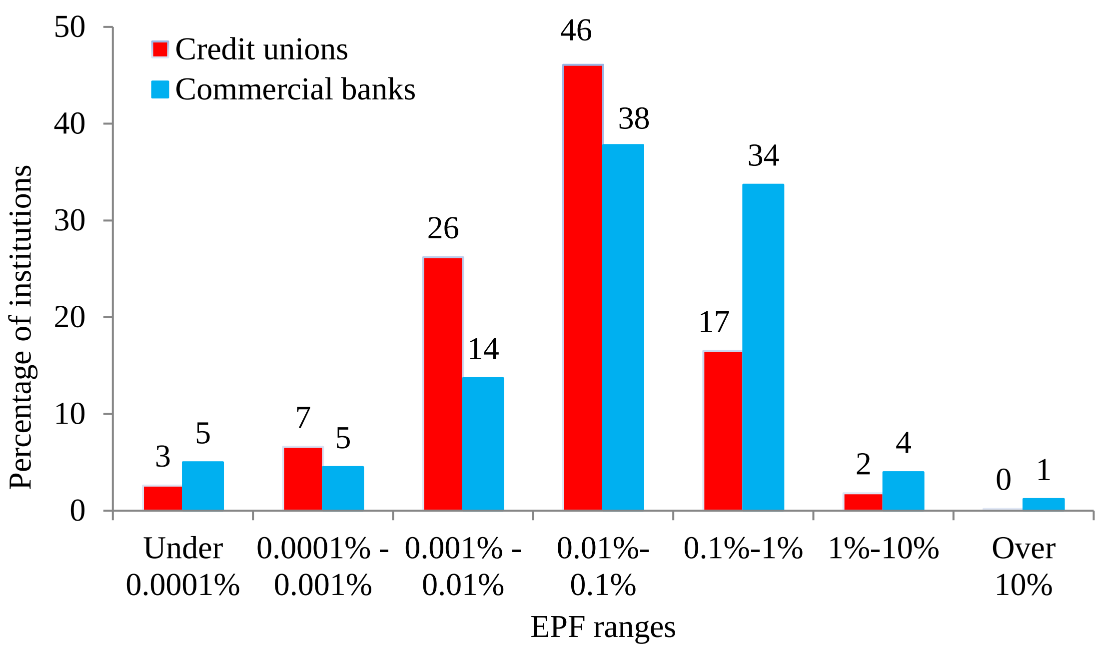


Figure 5 focuses on risky credit unions and banks. The bars there show the percent of smallish and medium credit unions and banks whose EPFs exceeded 0.10 percent for the selected years. Recall that the same logit estimates were used for each year. Reassuringly, the yellow bars for 1990 and the red bars for 2010 were the tallest. We would expect EPFs to be higher when the economy and the financial sector were troubled.

Figure 5 also draws our attention to other aspects of these EPFs. First, same-size banks had larger EPFs than credit unions for each year. Second, EPFs rose more for banks than for credit unions when troubles beset the financial sector. Third, about the same percents of these banks were risky in 2010 as in 1990. Finally, during 2017 relatively few credit unions or banks were risky.

Figure 5

Percent of Credit Unions and Commercial Banks with EPFs > 0.10 Percent, by Size, 1990, 2000, and 2010

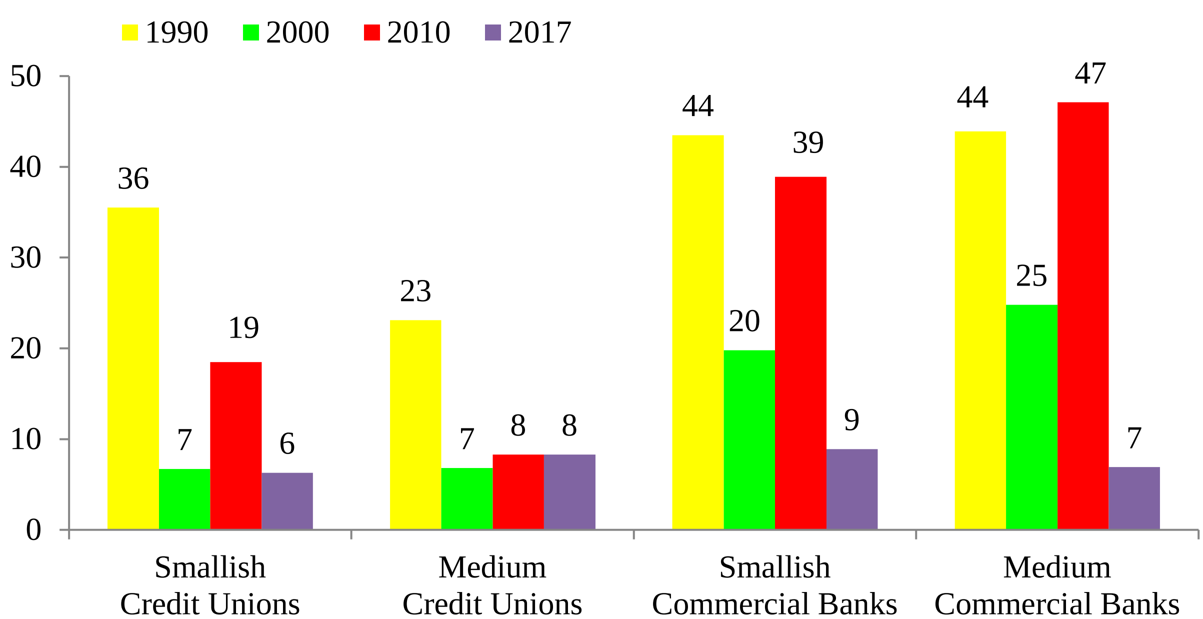
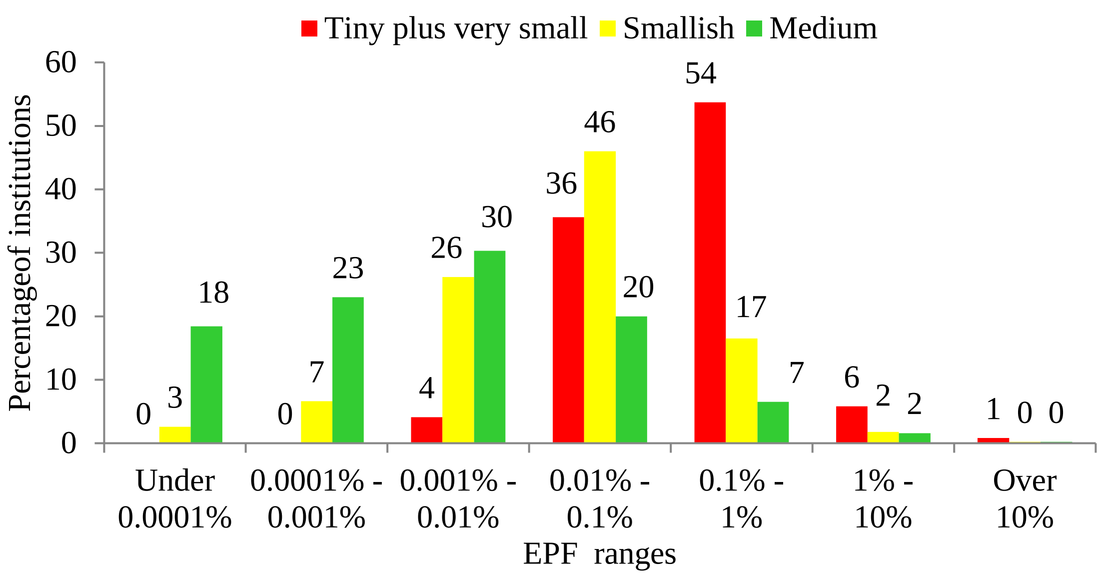


Figure 6 shows how the riskiness of credit unions during 2010 varied with size. There, medium credit unions (green) had lower EPFs than smallish credit unions, and they, in turn, had smaller EPFs than tine credit unions. Indeed, with the safe/risky dividing line at 0.10 percent, 60 percent of tine credit unions were risky almost all of the other tiny credit unions were in the bucket next to the dividing line.

Figure 6

Distributions of Estimated Probabilities of Failure (EPF)

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



7. Summary and implications

Economic diversification across lenders can reduce the risk that an economy's credit sector will become impaired. Differences in their external environments and internal choices have led to differences in credit unions' and banks' regulations, locations, organizational forms, business models, sizes, and portfolios. We regarded differences, if any, between credit unions' and banks' risks of failure as likely sources of economic diversification.

Therefore, we analyzed how much the measurable differences between credit unions and banks translated into differences in their failure probabilities and into differences in how much their risks were affected by external and internal factors. To quantify those differences, we estimated failure probability models for credit unions and for commercial banks during 1980-2016.

To do so, we first constructed a new panel of data for financial conditions of individual credit unions and their failures that spanned 1979-2016. The new dataset enabled our conducting the first, large-scale, long-term, econometric analysis of failures of credit unions.

We found that several of the factors long used to predict bank failures still do, and also helped predict credit union failures. But, we also found that some factors significantly raised failure probabilities of banks, while lowering them for credit unions, and vice versa. Having more residential mortgages raised risks at credit unions, but not at banks. Conversely, having more business loans presaged more failures of banks, but fewer failures of credit unions.

We used our estimated models to calculate distributions of expected probabilities of failure (EPFs) separately for credit unions and for banks. Generally and when controlling for size, banks tended to be appreciably riskier than credit unions. And, when the financial sector became troubled, failure probabilities at banks rose considerably more than they rose at credit unions.

Taken together, the differences between credit unions and banks in the amounts and in the responses of their failure risks add to the diversification of the credit sector. The size of the addition to diversification reflects the size of their differences, as well as the relative size of the credit union industry.

Recognizing how failure factors have affected risks of credit unions and of banks should inform both micro- and macro-prudential policies. One implication is that individual lenders' risks can be controlled with trade-offs. Making offsetting changes to risks ought to be more efficient than a "cap, don't trade" approach that sets limits without regard to offsets. The financial sector and the economy would benefit from regulation that promoted, or at least did not deter, a sufficiently diversified credit sector. Rather than focusing on failure probabilities of individual lenders, say through capital minimums, regulations might better adjust requirements for individual lenders in light of their contributions to the risks of the credit sector. Each of these policies would make better use of diversification, to the benefit of individual lenders, the credit sector, and, thereby, the economy.

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