The Determinants of Credit Union Failure: Insights from the United Kingdom*

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We use a proprietary data set on credit unions from the United Kingdom to develop an early-warning model of credit union failure. We find that a small set of financial attributes related to capital adequacy, asset quality, earnings performance, and liquidity, augmented with unemployment rates, reliably identifies failures within one year. Our results support the existing literature which, to date, has largely relied on data from the United States. This work therefore provides further evidence for establishing early-warning criteria for use by international regulators.

JEL Codes: G21, G28, G38.

1. Introduction

Credit unions provide an important source of credit and an avenue for saving in many countries around the world. At the end of 2016, over 68,000 credit unions located in 109 countries were serving 235 million people, or roughly 15 percent of economically active adults worldwide.[1] Since the mid-1990s, the global reach of these institutions has more than doubled and their assets have increased almost fourfold to $1.8 trillion (roughly 2 percent of world GDP). The

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[1]See World Council of Credit Unions Statistical Reports (available at http://www.woccu.org).

presence of credit unions is even more pronounced in several countries, including Ireland, Canada, and the United States, where these institutions reach more than a half of economically active adults.

In many countries, credit unions operate in rural or regional markets where access to traditional banks is more limited, thereby supporting economic activity that would otherwise go unfunded. Research has also shown that the presence of these institutions in general has implications for the real economy. For example, their presence leads commercial banks to offer higher rates on retail deposits (e.g., Hannan 2002) and lower rates on consumer loans (e.g., Feinberg 2003). These studies support the view that competition from credit unions can have direct benefits for consumers and the economy more broadly.[2] Therefore, their failure can have adverse effects not only on small, local pockets within a country but also on the wider economy to the extent that such failures affect competition. Understanding the early-warning signs of failure can therefore be important for regulators to avoid detrimental economic effects.

The literature examining the determinants of failure in the commercial banking sector is relatively widespread.[3] However, there is much less work on this issue for the credit union sector, especially outside the United States. One reason for this is because credit union failures in other countries are relatively rare.[4] Another explanation is that credit unions are less exposed to business cycle swings and

[2]Feinberg and Meade (2017) estimate the value of these direct benefits at $16 billion per year for the United States. Using a full general equilibrium analysis, they quantify the annual loss to GDP ($14.2 billion) and jobs (88,000) that result from a material (50 percent) reduction in the number of credit unions and competitive pressure on market rates that ensues. Their results have implications for understanding the economic impacts from a decline in credit unions and the merits of policies directed at fostering competition in banking markets more widely.

[3]Indeed, the large number of failures that occurred in the United States during the banking crisis in the late 1980s and early 1990s spawned an extensive body of work on the determinants of bank failure (e.g., Demirguc-Kunt 1989; Whalen 1991; Cole, Cornyn, and Gunther 1995; Cole and Gunther 1995; Sahajwala and Van den Bergh 2000; Wheelock and Wilson 2000). Studies investigating the determinants of bank failure during the 2007–09 financial crisis confirm that many of the factors explaining failure in the earlier crisis also contributed to failure in the more recent crisis (e.g., see Cole and White 2012).

[4]Rather than let credit unions fail, most jurisdictions have tended to transfer troubled credit unions to healthier ones (e.g., Jones 2010; McKillop, Ward, and Wilson 2011).

are better able to withstand shocks to their balance sheets (e.g., Smith and Woodbury 2010).[5]

Using regulatory data on credit unions in the United Kingdom, we investigate the determinants of failure within the U.K. credit union sector, which, to our knowledge, has not been examined previously. We adopt the framework employed in many of the aforementioned studies on commercial bank failure and use CAMEL factors (capital adequacy, asset quality, management, earnings performance, and liquidity) to develop an early-warning model of credit unions that failed between 2003 and 2015. Recent studies evaluating distress in mutually owned institutions, analogous to U.K. credit unions, employ similar techniques and find that CAMEL factors are helpful in identifying trouble early (Fiordelisi and Mare 2013; Francis 2014; Mare 2015). While our analysis focuses on the United Kingdom, it has implications for supervisory oversight in other countries where credit unions have a material presence, such as Australia, Canada, and Ireland.[6]

Despite playing a smaller role than traditional banking institutions in providing credit and deposit services, U.K. credit unions remain firmly on the radar of prudential supervisors given the important role they play in supporting local economies.[7] They do this mainly by supplying credit to consumers who typically find it difficult to borrow from traditional financial institutions, thus fostering economic activity that might otherwise go unfunded (Jones 2016).[8]

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[5]On the other hand, in the United States, where credit union failures have been more common, studies find that both macroeconomic and firm-specific factors have contributed to the demise of several thousand federally insured credit unions (e.g., see Wilcox 2005, 2007). These studies also show that the failure rates and the underlying drivers for these institutions' demise were not dissimilar to those for small, federally insured commercial banks in the United States.

[6]At the end of 2016, credit unions in Australia, Canada, and Ireland were serving approximately 20 percent, 50 percent, and 75 percent of economically active adults, respectively. See the World Council of Credit Unions 2016 Statistical Report (available at http://www.woccu.org/documents/2016_Statistical_Report).

[7]The Bank of England's Prudential Regulation Authority (PRA) supervises roughly 500 credit unions with close to two million members and £3 billion in assets. Monitoring the health of individual credit unions and the sector overall is part of the PRA's overall remit and is consistent with its primary safety and soundness objective.

[8]As discussed below, U.K. credit unions are also restricted as to the amount and duration of loans they can make to one borrower. This means that the vast

In the United Kingdom the credit union sector continues to garner attention in light of government efforts to widen financial inclusion and promote effective competition in the banking sector (e.g., see Hope 2010; Jones 2016), further motivating our U.K. focus.

Our paper evaluates the characteristics of failed credit unions one year prior to their demise.[9] To define credit union failure, we use a data set on institutions that have been referred to the U.K. Financial Services Compensation Scheme (FSCS) for depositor payout as part of the formal administration process.[10] We combine this information with annual regulatory report data to create a comprehensive database of credit union failures and financial statement information covering Great Britain and Northern Ireland for the period 2002 to 2015. We supplement this data set with unemployment rates to examine their contribution to credit union condition.

Consistent with the bank failure literature, we find that a small set of financial attributes related to capital adequacy, asset quality, earnings performance, and liquidity is significant in explaining credit union failure. Our analysis highlights the relative importance of each feature in explaining credit union failure. While capital adequacy plays a prominent role, our contribution is that we also show that the other factors, including the proportion of unsecured loans as well as national and regional unemployment rates, are important for characterizing failure. Out-of-sample performance results indicate that this parsimonious set of firm-level characteristics, along with unemployment measures, classifies failures reliably while keeping false positive (type II) error rates at modest levels. Overall, these

majority make only small consumer loans and not residential mortgages, which have historically been a particular source of risk in the commercial banking sector (e.g., Antoniadis 2017).

[9] Our focus on a one-year forecast horizon is consistent with standard practices in modeling default, including the standards in the Basel Capital Accord, and therefore may be of more interest to international supervisors. We also describe results of longer-term (two- and three-year) models below in our robustness checks.

[10] Defining failures based on FSCS referrals helps overcome potential endogeneity problems that can arise when failure events are proxied by financial measures, such as a fall in capital ratios or the incurrence of a material loss. Section 3 provides more background on the FSCS referral process and its relationship with credit union insolvency.

results highlight the significance of other sources of risk in addition to capital adequacy that should be considered when developing early-warning criteria for credit union soundness.

The remainder of this paper proceeds as follows. Section 2 provides basic background on the credit union sector in the United Kingdom. Section 3 describes our data set, empirical approach, and framework for evaluating model performance. Section 4 discusses results, while section 5 reviews model performance. Section 6 concludes.

2. Background on U.K. Credit Unions

Credit unions are not-for-profit financial cooperatives, established to meet the economic and social goals of their members. Due to charter restrictions, they do not conduct business with the general public, but instead serve a group of people characterized by a common bond, e.g., belonging to a particular community or sharing the same employer. For these reasons, they are usually concentrated geographically and their members' payment capacities can be subject to local economic conditions.

Credit unions provide savings products and, in general, small consumer-oriented loans. They are subject to stringent lending restrictions on the amounts that they can lend and the periods of such loans, which means that less than 5 percent of all credit unions in the United Kingdom can make residential real estate loans.[11] Importantly, they are also not subject to the same market pressures for growth and earnings performance as for-profit financial institutions. Nevertheless, they still face pressures from regulatory

[11] In particular, small, version 1 credit unions (i.e., those with capital under £1 million and less than 3,000 members), which comprise over 95 percent of the U.K. credit union sector, cannot lend to any one member more than £15,000 in excess of the member's deposit and cannot lend for a period of more than five years where unsecured and ten years where secured. All other credit unions, known as version 2 credit unions, cannot lend for a period of more than ten years where unsecured and twenty-five years where secured. In addition, these institutions cannot have exposure to any one member of more than £15,000 in excess of that member's deposit or an amount equal to 1.5 percent of capital in excess of that member's shares, whichever is greater. These limitations mean that only version 2 credit unions have the ability to make residential mortgage loans.

requirements to maintain minimum levels of capital and liquidity.[12] If a credit union breaches such minimums, it is required to undertake corrective actions or can be subject to more supervisory intervention, including closure.

3. Data and Empirical Approach

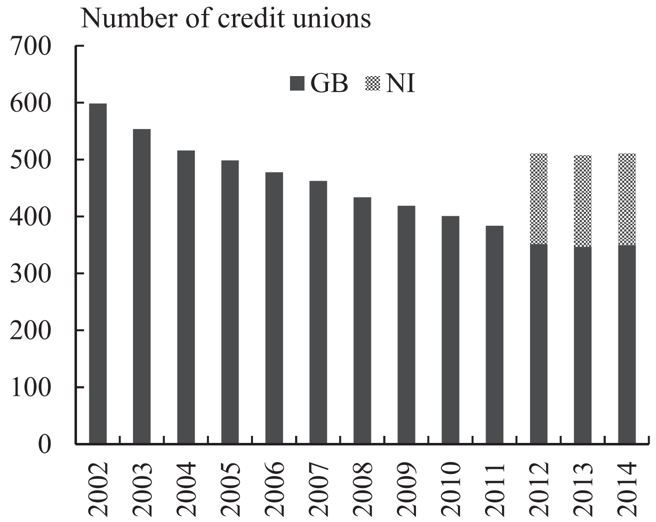
We use annual data (spanning 2002 to 2015) from credit unions' regulatory submissions to the U.K. Financial Services Authority (FSA) (from 2002 to 2013) and Prudential Regulation Authority (PRA) (since 2013). These submissions include details on a credit union's assets and liabilities, profit and loss, solvency, and liquidity positions. The data set is an unbalanced panel containing roughly 6,600 firm-year observations covering information on all credit unions in Great Britain for the years 2002 to 2014 and Northern Ireland for the years 2012 to 2014.

Figure 1 shows that, from 2002 to 2012, the number of credit unions in Great Britain (GB) declined from almost 600 to less than 400 due to mergers with other credit unions and, to a lesser extent, several failures (defined below). The number of credit unions jumped to more than 500 in 2012 as the scope of the U.K. supervisor's oversight expanded to include institutions in Northern Ireland (NI). Figure 2 shows that with the inclusion of NI credit unions, the assets of U.K.-supervised credit unions increased fivefold from less than £0.5 billion in 2002 to more than £2.5 billion at the end of 2014.

We define credit union failure to be the event when an institution was referred to the FSCS for depositor payout. FSCS protection was first extended to U.K. credit unions in 2002 when regulation of the sector was completely transferred from the Registry of Friendly

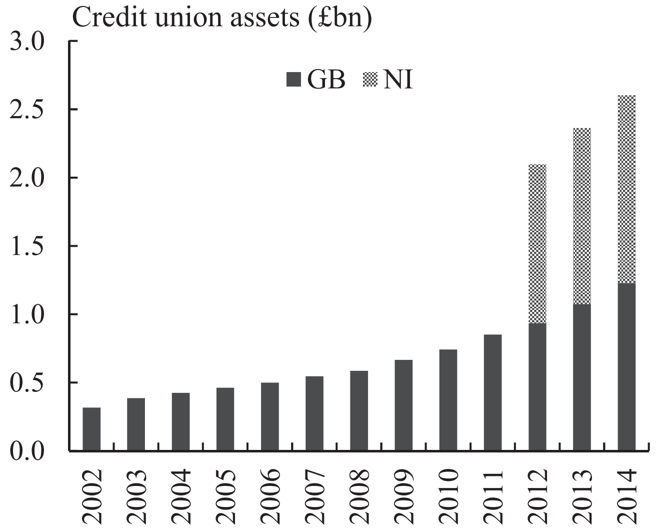
[12]For example, starting in 2013, small, version 1 credit unions (with fewer than 5,000 members and assets under £5 million) were required to maintain capital of at least 3 percent of total assets. This increased to 5 percent for large, version 1 institutions (with members from 5,000 to 10,000 and with assets of between £5 and £10 million). All other (version 2) credit unions were subject to an 8 percent risk-adjusted capital to total asset requirement, where risk-adjusted capital equaled capital plus provision for bad and doubtful debt less the specific provision for bad and doubtful debt. Credit unions were required to hold a liquidity ratio of at least 10 percent at all times.

Figure 1. Number of Credit Unions



Source: Bank of England.

Figure 2. Size of the U.K. Credit Union Sector



Source: Bank of England.

Societies to the FSA. The process of referring a credit union to the FSCS depends on two conditions being met: (i) the credit union must be insolvent (i.e., it reports a capital deficit) and (ii) the credit union has no realistic plan in place to rectify this situation in a timely manner.

Under these circumstances, the only option available is a winding up, which requires an insolvent credit union to appoint an insolvency practitioner to assist with the sale of assets and settle creditors' claims. Once this occurs, regulatory actions are taken to adjust the troubled credit union's permissible deposit-taking and lending activities and to restrict its ability to make any distributions. These measures help prevent capital deficiency from increasing and ultimately protect existing members and the FSCS. Within ten days of appointing an insolvency practitioner, the credit union must register this appointment with the Court, which then issues an official winding-up order, triggering FSCS referral by the PRA (FSA prior to 2013). Because the time between insolvency and referral is short and since the practices have remained unchanged since 2002, we believe that using FSCS referral consistently captures the timing and occurrence of failure relatively well over our sample period. Using this strategy, we identified eighty-five failures, although only sixty-eight are included in our data set due to a lack of corresponding regulatory return information for seventeen institutions. Table 1 reports the annual failure rates from 2003 to 2015, which averaged around 1 percent but varied considerably, peaking in the two years in the immediate aftermath of the crisis.[13]

3.1 Explanatory Variables

Table 2 summarizes our candidate CAMEL variables and the expected association with failure. To gauge capital adequacy, we include a simple capital ratio—equal to total capital as a percentage

[13]We also find that no one region stood out as contributing disproportionately to firm failure. The distribution of failures across the United Kingdom was as follows (with percentage of total in parentheses): Greater London: 5 (7%); East Midlands: 5 (7%); Eastern England: 2 (3%); Northeast: 5 (7%); Northwest: 7 (10%); Northern Ireland: 1 (1%); Scotland: 7 (10%); Southeast: 2 (3%); Southwest: 6 (9%); Wales: 4 (6%); West Midlands: 9 (13%); Yorkshire and the Humber: 6 (9%); not assigned: 9 (13%). Total: 68 (100%).

Table 1. Credit Union Failures (2003 to 2015)

Year	Total Credit Unions	Failures[a]	Failure Rate[b]
2003	625	3	0.48%
2004	584	1	0.17%
2005	543	1	0.18%
2006	532	5	0.94%
2007	512	8	1.56%
2008	497	6	1.21%
2009	468	6	1.28%
2010	452	10	2.21%
2011	428	8	1.87%
2012	405	6	1.48%
2013	518	6	1.16%
2014	514	2	0.39%
2015	514	6	1.17%
Total	6,592	68	1.03%

Sources: Bank of England and authors' calculations.
[a]Institutions referred to the FSCS.
[b]Number of failures divided by total number of credit unions.

of total assets—which is analogous to the leverage ratio for banks. The intuition for its use is that lower capital ratios make institutions more vulnerable to shocks, since they have lower capacity to absorb unexpected loan losses or material declines in asset values. We expect this measure to be negatively associated with the probability of default.

With respect to asset quality, we evaluate four variables. First, we examine the proportion of loans that are in arrears. The arrears rate measures the quality of a firm's existing loan book, with a higher arrears rate indicating potential losses on these loans. We use two distinct ratios: one based on loans between three and twelve months in arrears and another based on loans more than twelve months in arrears. Second, we use the ratio of provisions to loans to capture credit unions' own assessments of losses embedded in their loan portfolios. Third, we consider the ratio of unsecured loans to total assets

Table 2. CAMEL Predictors of Failure

CAMEL Factor	Definition[a]	Expected Association with Failure
Capital Adequacy:		
Simple Capital Ratio	Total Capital/Total Assets	–
Asset Quality:		
Arrears 3–12 Months	Net Liabilities 3–12 Months in Arrears/Total Net Liabilities[b]	+
Arrears > 12 Months	Net Liabilities > 12 Months in Arrears/Total Net Liabilities[b]	+
Provision Coverage	(General + Specific Provisions)/Net Liabilities in Arrears	–
Unsecured Loans	Unsecured Loans/Total Assets	+
Management:		
Size	Natural Log of Total Assets	–
Cost-to-Income	Total Expenditure/Total Income	+
Admin. Expense	Administrative Expense/Total Assets	+
Members	Number of Qualifying Members	+/–
Full-Time Staff	Number of Full-Time Employees	+/–
Earnings:		
Return on Assets	After-Tax Profit (Loss)/Total Assets	–
Liquidity:		
Liquidity Ratio	Total Liquid Assets[c]/Total Relevant Liabilities[d]	+/–
Loans to Deposits	Total Loans/Total Members' Share Balance	+/–

[a]Unless otherwise noted, all measures are expressed as percentages and have been multiplied by 100.
[b]Net liabilities equal total loans plus accrued interest less the members' share balances used to secure the loan.
[c]Total liquid assets equal the sum of qualifying cash and bank balances, investments realizable within eight days, unused committed facilities, and unused overdrafts.
[d]Total relevant liabilities equal the sum of unattached shares and liabilities with an original or remaining maturity of less than three months.

as a proxy for credit risk exposure overall.[14] A higher ratio suggests relatively greater credit risk. We expect these three proxies for asset quality to be positively associated with the likelihood of failure. As a fourth proxy for asset quality, we considered loan loss provisions as a percentage of arrears. The relationship between this measure and failure is ambiguous. On the one hand, a relatively high coverage ratio may imply that credit unions have more than adequately provided for losses embedded in past-due loans. If that is the case, then we would expect the relationship with failure likelihood to be negative. If, on the other hand, higher coverage ratios imply a deterioration in asset quality overall, then we might expect to find a positive association with the likelihood of failure.

We use five different measures to capture the third CAMEL variable, management quality. We use credit union size (measured by the natural log of total assets), and two measures of efficiency, approximated by the ratio of total costs to total revenue (income) and the ratio of total administrative expenses to total assets. We expect size to be inversely correlated with probability of failure based on the idea that larger credit unions may be better diversified across borrowers and geographic location. We expect the two efficiency ratios to be positively associated with failure, with higher (lower) values of these indicators suggesting worse (better) managerial quality. Finally, we include a credit union's number of members and of paid staff as additional proxies for management quality.

Prior research has found that measures of earnings performance are useful in explaining bank failure. To measure earnings performance, we use the ratio of after-tax net income to total assets for our fourth CAMEL proxy. We expect a negative relationship between this ratio and failure.

Finally, for our fifth CAMEL indicator, liquidity, we consider the standard liquidity ratio, defined as liquid assets to total liabilities (see table 2 for definition) and the ratio of loans to deposits. The expected effect of the standard liquidity ratio on failure is, ex ante, ambiguous. On the one hand, it could be inversely associated with the likelihood of failure to the extent that liquid assets provide a useful secondary source of liquidity that credit unions can use to

[14]Regulatory data limitations prevent a finer breakdown of the loan portfolio by type.

Table 3. Summary Statistics[a]

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Size (Log of Total Assets)	6,601	12.89	1.67	4.46	18.71
Capital Ratio (%)	6,591	8.74	8.17	−11.36	48.01
Arrears 3–12 Months[b] (%)	6,448	9.65	14.33	0.00	97.24
Arrears over 12 Months[b] (%)	6,486	7.49	14.24	0.00	85.71
Unsecured Loans[c] (%)	6,306	41.51	24.81	2.59	100.39
Provision Coverage (%)	5,557	179.16	297.13	36.28	2,200.00
Cost-to-Income Ratio (%)	6,601	82.84	33.73	16.31	230.68
Admin. Expense (%)	6,601	6.82	10.08	0.00	60.43
Membership (000's)	6,578	1.76	13.49	0.00	1,069.79
Full-Time Staff	6,607	2.92	9.87	0.00	663.00
Return on Assets (%)	6,601	1.61	3.47	−13.29	13.27
Liquidity Ratio (%)	6,564	77.07	63.00	6.70	501.99
Loans-to-Deposits Ratio (%)	6,560	68.56	28.35	10.93	159.83
National Unemployment Rate	6,601	6.18	1.27	4.80	8.10
Regional Unemployment Rate	6,018	6.31	1.56	3.40	10.60

[a]Bank-level characteristics based on measures winsorized at the 1st and 99th percentiles.
[b]Percentage of total net loans to members.
[c]Percentage of total assets.

satisfy unexpected liquidity needs. On the other hand, inefficiencies may arise from holding higher proportions of liquid assets, which could weigh on earnings performance and subsequently contribute to the likelihood of failure. Regarding our second measure, the ratio of loans to deposits, while a higher ratio implies a potentially less liquid balance sheet, it could indicate a more efficient use of funding, which could improve earnings and capital. As a result, the expected impact on failure is also, ex ante, ambiguous.

3.2 Descriptive Statistics

Table 3 reports summary statistics on our CAMEL variables, while table 4 reports mean equality tests between failures and survivors from a simple univariate analysis for our main candidate

Table 4. Mean Comparison Tests

Variables	Failures		Survivors		Mean Equality Test (t-test, Unequal Variances)	
	Mean	Obs.	Mean	Obs.	Difference	p-value
Size (Log of Total Assets)	11.88	421	12.96	6,180	−1.08	0.00
Capital Ratio (%)	4.04	418	9.06	6,173	−5.02	0.00
Arrears 3–12 Months[a] (%)	13.82	463	9.33	5,985	4.49	0.00
Arrears over 12 Months[a] (%)	10.57	466	7.25	6,020	3.32	0.00
Unsecured Loans[b] (%)	11.03	336	7.59	5,401	3.44	0.00
Provision Coverage (%)	50.93	399	40.87	5,907	10.06	0.01
Cost to Income (%)	107.52	421	81.16	6,180	26.36	0.00
Admin. Expense (%)	11.87	421	6.48	6,180	5.39	0.00
Membership (000's)	0.63	419	1.84	6,159	−1.21	0.00
Full-Time Staff	3.22	421	2.90	6,180	0.32	0.83
Return on Assets (%)	−0.55	421	1.76	6,180	−2.31	0.00
Liquid Asset Ratio (%)	74.78	413	77.23	6,151	−2.45	0.32
Loans to Deposits (%)	77.93	416	67.92	6,144	10.01	0.00

[a]Percentage of total net loans to members.
[b]Percentage of total assets.

variables.[15] The tests suggest that failed credit unions are generally smaller, less well capitalized, and less profitable. They also tend to have weaker asset quality (as reflected by higher arrears rates, loan loss provisions, and unsecured loans), poorer management efficiency ratios (i.e., higher cost-to-income ratios), and weaker liquidity positions (higher loan-to-deposit ratios).

3.3 Modeling Failure

Following Shumway (2001), we model failure using a multi-period logit model. Since we are interested in whether the CAMEL variables help anticipate failure regardless of firm or time period, we pool the data across firms and over years. This approach allows for time variation in the explanatory variables and treats a credit union's condition as a function of its latest financial measures (as derived from annual regulatory returns).[16] The probability of credit union failure over the next year is equal to

$$P\left(Y_{i,t} = 1 | X_{i,j,t-1}\right) = \frac{1}{1 + exp(-\beta_0 + \sum_{j=1}^{J} \beta_j X_{i,j,t-1})}, \qquad (1)$$

where $Y_{i,t}$ is an indicator variable equal to one if credit union i fails (i.e., referred to the FSCS for payout) in year t and equal to zero if the credit union remains active. The term in the denominator on the right-hand side, $\sum_{j=1}^{J} \beta_j X_{i,j,t-1}$, represents a linear combination of our j explanatory variables, which, discussed below, includes CAMEL factors lagged by one year. For early-warning use, this specification helps to understand what factors differentiate failed from successful credit unions and how their state changes in the run-up to FSCS referral.[17]

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[15] We winsorized all bank-level variables at the 1st and 99th percentiles to mitigate the influence of extreme outliers.

[16] Poghosyan and Cihak (2011) employ a similar approach to examine the determinants of bank distress in Europe, while Cole and Wu (2009) extend this approach to investigate factors explaining U.S. commercial bank failures during the banking crisis of the late 1980s and early 1990s.

[17] Our baseline model employs explanatory variables lagged one year. As a robustness check (discussed below), we also tested specifications with two- and three-year lags. The tests produced results that were broadly similar but weaker in terms of statistical significance, indicating that the predictive power of these models diminishes as the horizon over which failures are predicted increases.

Table 5. Classification Matrix

Signal Issued One Year Prior (at time t–1)	Forecasted Event $F_{i,t-1}$	Actual Failure Event $Y_{i,t}$	
		Failure	**Non-failure**
Yes ($F_{i,t-1} = 1$)	Failure	True Positive (TP)	False Positive (FP)
No ($F_{i,t-1} = 0$)	Non-failure	False Negative (FN)	True Negative (TN)

To estimate this equation, we consider the possibility that individual credit union observations may be correlated across time and that the errors across institutions may not be identically distributed. Ignoring this possibility would lead to downward-biased estimates of standard errors of the coefficients. To deal with this issue, we use logistic models that are robust to clustering of errors at the firm level.

3.4 Evaluating Model Performance for Supervisory Use

To evaluate our failure models and the potential tradeoffs in the context of early-warning systems, we rely on the standard type I versus type II error tradeoff approach used in the banking literature (e.g., Poghosyan and Cihak 2011; Aikman et al. 2014; Betz et al. 2014). This involved choosing a threshold probability, $\pi \in [0, 1]$, above which our model issues a "signal," warning that a credit union is vulnerable and at risk of failure. To facilitate evaluation of such signals, we transform the probability of failure that derives from our logistic model based on data reported at period $t-1, p_{i,t-1}$, into another binary variable $F_{i,t-1}$ that equals one if $p_{i,t-1}$ exceeds π and zero otherwise. The association between the forecast (signal) $F_{i,t-1}$ and the actual failure, as represented by $Y_{i,t}$, can be summarized using a classification matrix as set out in table 5.

In our case, a type I error occurs when our model fails to classify a credit union failure correctly, i.e., the model does not issue a warning signal when a failure is imminent. A type II error results when a healthy credit union is mistakenly forecast to fail. Relating this to the classification matrix above, type I errors are calculated as T_1 = *FN/(TP+FN)*, and type II errors as T_2 = *FP/(FP+TN)*. To compare and contrast model performance, we use measures from receiver operating characteristic (ROC) curves and the area under the ROC curve (AUROC). The ROC curve plots, for the complete range of threshold probabilities $\pi \in [0, 1]$, the conditional probability of positives to the conditional probability of negatives:

$$ROC = \frac{PR\,(Y_{i,t} = 1|F_{i,t-1} = 1)}{1 - PR\,(Y_{i,t} = 0|F_{i,t-1} = 0)}, \tag{2}$$

where $Y_{i,t}$ and $F_{i,t-1}$ are as defined above. In this regard, the ROC curve shows the tradeoff between the benefits (i.e., avoiding the costs that derive from missing a failed credit union) and the costs from misclassifying too many healthy firms: the higher the AUROC, the better the model.

4. Results

To establish our baseline results, we ran a series of specifications involving CAMEL variables. Table 6 presents the results of models employing CAMEL components separately (models 1–5) and our preferred baseline model (model 6) including measures capturing all five CAMEL factors. The results of the component models are consistent with expectations and generally show that each aspect, when included separately, is statistically significant in explaining failure. Asset size (model 1), capitalization (model 2), and earnings (model 4) are negatively associated with the probability of failure, which accords with findings from bank failure research (e.g., Cole, Cornyn, and Gunther 1995; Cole and Wu 2009; Poghosyan and Cihak 2011).[18] The positive signs on the arrears rates and the proportion of unsecured loans (model 3) imply that the likelihood of failure increases as asset quality deteriorates. The positive sign on the loan-to-deposit ratio (model 5) suggests that the likelihood of failure increases as liquidity risk increases.

[18] We also found that the cost-to-income ratio was positively associated with the probability of failure, suggesting that credit unions with less-efficient management teams (as measured by a higher cost-to-income ratio) are more likely to fail sometime in the upcoming year. We excluded this variable from our baseline specification due to the high correlation (see table 9 in the appendix) with our earnings measure, ROA, to mitigate issues with multicollinearity. This was also true with respect to the provision coverage ratio, which is highly correlated with the arrears measures included in the preferred specification.

Table 6. One-Year Failure Model

Variables	**Model 1 Management**	**Model 2 Capital**	**Model 3 Asset Quality**	**Model 4 Earnings**	**Model 5 Liquidity**	**Model 6 Baseline**
Size	−0.2923***					−0.3027**
	(0.0728)					(0.1535)
Capital Ratio		−0.1591***				−0.0948**
		(0.0366)				(0.0390)
Arrears > 12 Months			0.0242***			0.0141**
			(0.0046)			(0.0065)
Unsecured Loans			0.0264***			0.0218***
			(0.0058)			(0.0072)
ROA				−0.2095***		−0.0682
				(0.0226)		(0.0417)
Liquidity Ratio					−0.0004	0.0035
					(0.0041)	(0.0032)
Loan-to-Deposit Ratio					0.0182***	0.0106*
					(0.0035)	(0.0058)
Constant	−1.0553	−3.9365***	−6.4041***	−4.7022***	−6.1056***	−2.8441*
	(0.8980)	(0.1591)	−0.3741	(0.1509)	−0.4026	(1.6626)

(continued)

Table 6. (Continued)

Variables	Model 1 Management	Model 2 Capital	Model 3 Asset Quality	Model 4 Earnings	Model 5 Liquidity	Model 6 Baseline
No. of Observations	5,725	5,720	5,331	5,725	5,666	5,309
Wald chi^2	16.134	18.893	59.536	85.818	27.185	132.137
Probability > chi^2	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.0173	0.0922	0.0685	0.0913	0.0257	0.1778
Log Likelihood	−286.489	−256.017	−237.438	−264.918	−278.919	−201.512
AIC	576.979	516.034	480.875	533.835	563.837	419.024
BIC	590.284	529.337	500.619	547.140	583.764	471.641
AUROC Curve	0.6304	0.7698	0.7494	0.7749	0.6760	0.8364

Notes: This table reports results of the logistic regression model $\log[p_{i,t}/(1 - p_{i,t})] = \beta_0 + \Sigma_{j=1}^{N} \beta_j X_{j,i,t-1} + \varepsilon_{i,t}$, where $p_{i,t} = Prob(Y_{i,t} = 1|X_{j,i,t-1})$ is the probability that credit union i is referred to the FSCS for payout in year t given the vector of j explanatory variables at time $t - 1$. Definitions of all explanatory variables are listed in table 2. Standard errors are reported in parentheses below their coefficient estimates and adjusted for both heteroskedasticity and within correlation clustered at the credit union level. The area under the ROC curve is a measure of how well each specification can distinguish between failures and survivors, with larger areas representing better performance. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively.

The baseline model (model 6) includes all five CAMEL components and shows that the signs on the coefficients are in line with expectations. It also shows that including all CAMEL elements improves the fit and in-sample classification power of the model. Our pseudo R-squared for the baseline model increases from, on average, 0.06 (across models 1–5) to 0.18, which is comparable with the fit of similar models in the bank failure literature (e.g., Cole and White 2012; De Young and Torna 2012; Antoniades 2017). The area under the ROC curve shows that the classification of failures and survivors improves when using all five versus employing just one of the CAMEL aspects. Overall, the results suggest CAMEL factors together are useful in characterizing future failures.

Previous literature shows that macroeconomic conditions may be important drivers of banking crises (e.g., Beck, Demirguc-Kunt, and Levine 2006; Cihak and Schaeck 2007) and individual bank failures (e.g., De Young and Torna 2012). Lower rates of unemployment, for example, can be associated with a less volatile macroeconomic environment and, in turn, a lower likelihood of bank-level failure. To test if macroeconomic conditions affect the viability of credit unions, we include national and regional unemployment rates as additional controls. Table 7 reports the results of including these additional controls. Model 6A shows that the lagged national unemployment rate is positively correlated with failure. Indeed, the inclusion of national unemployment improves the in-sample fit of the baseline model as suggested by increases in the pseudo R-squared measures and the area under the ROC curve for each model.

Credit union failure may also be sensitive to regional indicators, given the lack of diversification of its membership. Model 6B shows that regional unemployment is positively associated with the likelihood of failure. The results also indicate that the fit of the baseline models improves with the inclusion of regional unemployment.[19]

[19]Comparisons of Akaike information criterion (AIC) and Bayesian information criterion (BIC) measures across each of the models also confirm that the inclusion of unemployment measures is especially helpful in improving in-sample fit. Both measures for all models that include unemployment rates are lower than those for the corresponding baseline model.

Table 7. One-Year Baseline Failure Model Augmented with National and Regional Unemployment Rates

Variables	Model 6 One-Year Baseline	Model 6A National Unemployment	Model 6B Regional Unemployment
Size	−0.3027**	−0.5340***	−0.3764**
	(0.1535)	(0.1567)	(0.1522)
Capital Ratio	−0.0948**	−0.1073***	−0.1197***
	(0.0390)	(0.0352)	(0.0389)
Arrears > 12 Months	0.0141**	0.0099	0.0101
	(0.0065)	(0.0064)	(0.0072)
Unsecured Loans	0.0218***	0.0245***	0.0167**
	(0.0072)	(0.0077)	(0.0084)
ROA	−0.0682	−0.0483	−0.0489
	(0.0417)	(0.0411)	(0.0427)
Liquidity Ratio	0.0035	0.0040	0.0054*
	(0.0032)	(0.0030)	(0.0028)
Loan-to-Deposit Ratio	0.0106*	0.0122**	0.0133**
	(0.0058)	(0.0054)	(0.0056)
National Unemployment		0.5333***	
		(0.1309)	
Regional Unemployment			0.4221***
			(0.1179)
Constant	−2.8441*	−3.5394**	−4.7735***
	(1.6626)	(1.7054)	(1.7469)
No. of Observations	5,309	5,309	4,867
Wald chi^2	132.136	152.887	117.1173
Probability > chi^2	0.0000	0.0000	0.0000
Pseudo R^2	0.1778	0.2084	0.1838
Log Likelihood	−201.512	−194.010	−153.162
AIC	419.023	406.021	324.324
BIC	471.641	465.216	382.736
AUROC Curve	0.8364	0.8693	0.8713

Notes: This table reports results of the logistic regression model $\log[p_{i,t}/(1-p_{i,t})] = \beta_0 + \Sigma_{j=1}^{N}\beta_j X_{j,i,t-1} + \varepsilon_{i,t}$, where $p_{i,t} = Prob(Y_{i,t} = 1|X_{j,i,t-k})$ is the probability that credit union i is referred to the FSCS for payout in year t given the vector of j explanatory variables at $t-1$. Definitions of all explanatory variables are listed in table 2. Standard errors are reported in parentheses below their coefficient estimates and adjusted for both heteroskedasticity and within correlation clustered at the credit union level. The area under the ROC curve is a measure of how well each specification can distinguish between failures and survivors, with larger areas representing better performance. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively.

4.1 Robustness Checks

To assess the reliability of our baseline model, we employed a different measure of failure and a different lag structure on our explanatory variables. In general, our baseline results are robust to these changes.[20]

While using the administrative measure related to FSCS referral to define failure can help mitigate endogeneity issues that can arise when relying on financial metrics to proxy failure, it is also possible that our definition of failure could be biased if supervisors take actions ahead of FSCS referral in an attempt to avoid referral and soften losses to the FSCS. To address this possible bias, we employed a different measure of failure: we consider a credit union to have "failed" if it breached a capital-to-asset ratio threshold of 5 percent, 3 percent, or 0 percent.[21] Table 8, columns 1–3, reports the results of estimating separate models for each progressively lower threshold measure. In general, the results are qualitatively similar to the baseline results reported in table 6. However, one finding that stands out in these capital breach models is that the statistical significance of our earnings measure (ROA) is more prominent. This is not surprising given the role that earnings plays in influencing capital directly.

[20] We undertook a number of additional checks but do not report them to save space. Overall, the additional tests show that our baseline models are robust to including both time and region effects; including other macroeconomic controls (annual rates of GDP growth and inflation); and excluding version 2 credit unions, which are subject to more stringent capital requirements and intensive supervisory scrutiny and have the ability to underwrite residential real estate mortgages. All results are available upon request.

[21] Using this definition, our sample includes significantly higher failure rates, on average, compared with the 1 percent under the FSCS definition: 30 percent based on the 5 percent threshold, 17 percent based on the 3 percent threshold, and 5 percent based on the 0 percent threshold. It should be noted, however, that for twelve of the fourteen years in our estimation period, credit unions in the United Kingdom were not subject to a formal capital requirement. Instead, they were only required to operate with a positive net capital position. Beginning in 2013, U.K. credit unions were subject to a 3 percent capital-to-asset requirement, and it is for this reason that we elected to focus on thresholds around this level.

Table 8. Robustness Checks (one-year model with different left-hand-side variable; baseline two- and three-year models)

Variables	5% Threshold (1)	3% Threshold (2)	0% Threshold (3)	Two-Year Baseline (4)	Three-Year Baseline (5)
Size	−0.2499***	−0.2526***	−0.4107***	−0.5101***	−0.5231***
	(0.0320)	(0.0411)	(0.0714)	(0.1442)	(0.1258)
Capital Ratio	−0.4546***	−0.4037***	−0.2772***	−0.0425	−0.0743**
	(0.0291)	(0.0300)	(0.0221)	(0.0328)	(0.0298)
Arrears > 12 Months	−0.0061**	−0.0017	0.0065	0.0088*	0.0160***
	(0.0030)	(0.0035)	(0.0050)	(0.0052)	(0.0054)
Unsecured Loans	0.0009	0.0029	0.002	0.0133	0.0169**
	(0.0023)	(0.0028)	(0.0043)	(0.0083)	(0.0074)
ROA	−0.0504**	−0.0804***	−0.0815***	−0.1010**	−0.0298
	(0.0245)	(0.0262)	(0.0276)	(0.0442)	(0.0419)
Liquidity Ratio	−0.0006	−0.0010	−0.0029	−0.0122**	0.0029
	(0.0012)	(0.0014)	(0.0022)	(0.0054)	(0.0025)
Loan-to-Deposit Ratio	0.0053**	0.0031	0.0172***	0.0081	0.0086
	(0.0023)	(0.0025)	(0.0035)	(0.0079)	(0.0057)
Constant	4.8843***	3.4715***	1.8738**	1.4122	0.7777
	(0.4288)	(0.5147)	(0.8614)	−1.6544	(1.3636)

(*continued*)

Table 8. (Continued)

Variables	5% Threshold (1)	3% Threshold (2)	0% Threshold (3)	Two-Year Baseline (4)	Three-Year Baseline (5)
No. of Observations	5,309	5,309	5,309	4,556	3,888
Wald chi^2	437.427	322.676	333.4132	119.416	76.308
Probability > chi^2	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.4122	0.3820	0.4141	0.1571	0.1144
Log Likelihood	−1,909.505	−1,475.452	−585.2786	−220.611	−248.219
AIC	3,835.011	2,966.903	1,186.5572	457.223	512.439
BIC	3,887.628	3,019.520	1,239.1745	508.617	562.565
AUROC Curve	0.9215	0.9162	0.9253	0.8359	0.7891

Notes: Columns 1, 2, and 3 of this table report results of the logistic regression model $\log[p_{i,t}/(1-p_{i,t})] = \beta_0 + \Sigma_{j=1}^{N}\beta_j X_{j,i,t-k} + \varepsilon_{i,t}$, where $p_{i,t} = Prob(Y_{i,t} = 1|X_{j,i,t-k})$ is the probability that credit union i breaches a predetermined capital (to asset) ratio threshold in year t given the vector of j explanatory variables at time $t-1$. Columns 4 and 5 report results of the logistic regression model $\log[p_{i,t}/(1-p_{i,t})] = \beta_0 + \Sigma_{j=1}^{N}\beta_j X_{j,i,t-k} + \varepsilon_{i,t}$, where $p_{i,t} = Prob(Y_{i,t} = 1|X_{j,i,t-k})$ is the probability that credit union i is referred to the FSCS for payout in year t given the vector of j explanatory variables at time $t-2$ and $t-3$, respectively. Definitions of all explanatory variables are listed in table 2. Standard errors are reported in parentheses below their coefficient estimates and adjusted for both heteroskedasticity and within correlation clustered at the credit union level. The area under the ROC curve is a measure of how well each specification can distinguish between failures and survivors, with larger areas representing better performance. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively.

Pragmatic considerations related to supervisory use of early-warning models motivates our focus on a one-year-ahead model. We also evaluate how our baseline results hold under longer, two- and three-year horizons by altering the lag structure on our explanatory variables. Columns 4 and 5 of table 8 report the results of specifications that include variables lagged two and three periods before failure. The signs on all coefficient estimates remain unchanged. Comparisons of the pseudo R-squared and AUROC measures show that fit and classificatory power diminish over longer time horizons.

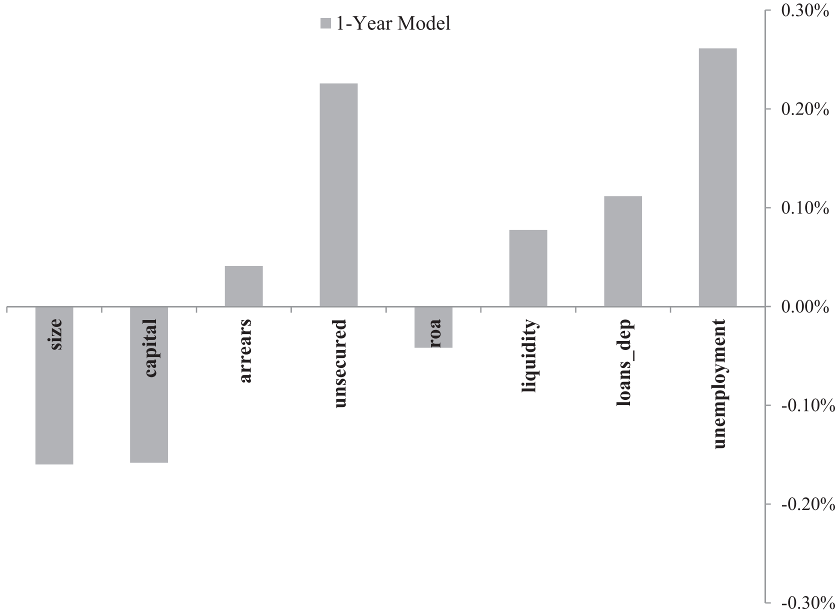
4.2 Economic Significance

The coefficients of the baseline model measure the direction of the impact on the probability of failure. It is difficult, however, to interpret the economic significance of each factor in explaining failure since the magnitude of the impact depends on the initial values of all independent variables and their coefficients. Following standard practice, we derive the economic impact of the individual CAMEL factors by computing the marginal effects at the sample average. In particular, we compute the change in the probability of failure for a one-standard-deviation change in each variable separately for each of the eight variables in the baseline model augmented with national unemployment, holding all other variables constant at their sample average.

Figure 3 shows the relative marginal effects of each covariate in our baseline model, supplemented with national unemployment rates.[22] The shaded bars represent the change in the probability of failure associated with a one-standard-deviation increase in each covariate, holding all other variables at the sample mean. The figure shows that asset quality (proportion of unsecured loans) and national unemployment rates have material influences on the likelihood of credit union failure, while size and capitalization play

[22] For completeness, we have included marginal effects on variables that are not statistically significant: ROA and the liquidity ratio.

Figure 3. Effect of a One-Standard-Deviation Change in Each Variable on Failure Probability

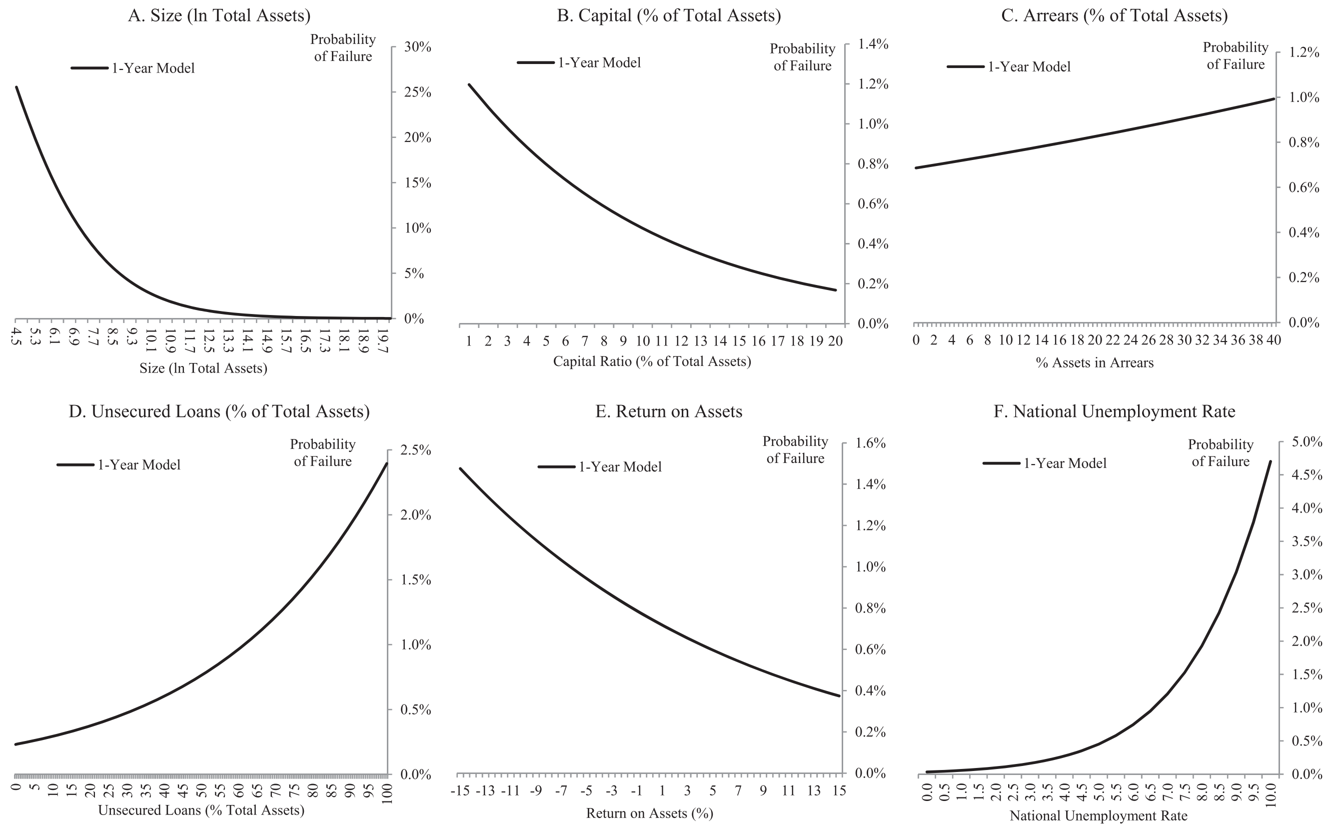


Source: Authors' calculations.

offsetting roles. Liquidity and earnings measures also play minor roles in contributing to failure.

As another way of illustrating economic significance, we report the marginal impacts separately for each of the CAMEL covariates and the national unemployment rate found significant in our augmented baseline models. Figure 4 reports the impacts on the likelihood of failure across a range of plausible values for each covariate separately, while holding all of the remaining independent variables at their sample average. Comparison of marginal effects across the significant determinants of credit union failure suggests that failure probabilities are more responsive to changes in capitalization (panel B) and unsecured loan proportions (panel D). These figures again illustrate the pronounced effects of unemployment and the importance of considering economic conditions for early identification of at-risk credit unions.

Figure 4. Marginal Effects of Explanatory Variables



Source: Authors' calculations.

5. Model Performance

This section reviews the ability of our estimated baseline model to classify failed and surviving credit unions correctly. We focus on evaluating performance in terms of the "usefulness" they provide in terms of minimizing costs associated with type I and type II errors and by comparing the area under receiver operating characteristic (ROC) curves. Better models under this approach would have a higher benefit (i.e., true positive, or "hit rate" on the vertical axis) at the same cost (i.e., false positive, or "false alarm rate" on the horizontal axis). Each false positive along the horizontal axis is associated with a threshold, meaning that the ROC curve measures show performance over all thresholds (not just a predetermined threshold, such as π discussed earlier). The area under the curve measures the likelihood that a randomly chosen failure event is ranked higher than a non-failure. A perfect ranking has an area equal to 1, while random chance has an area under the curve of 0.5.

5.1 In-Sample Classification Performance

The in-sample results reported in table 6 indicate that, while the baseline model has relatively high discriminatory power, performance improves with the addition of unemployment rates. In particular, the area under the ROC curve for the baseline model is roughly 84 percent and increases to 87 percent when augmented with national (or regional) unemployment rates. Overall, the in-sample results suggest that there could be scope for improving model performance by augmenting firm-level characteristics with unemployment rates.

5.2 Out-of-Sample Forecasting Performance

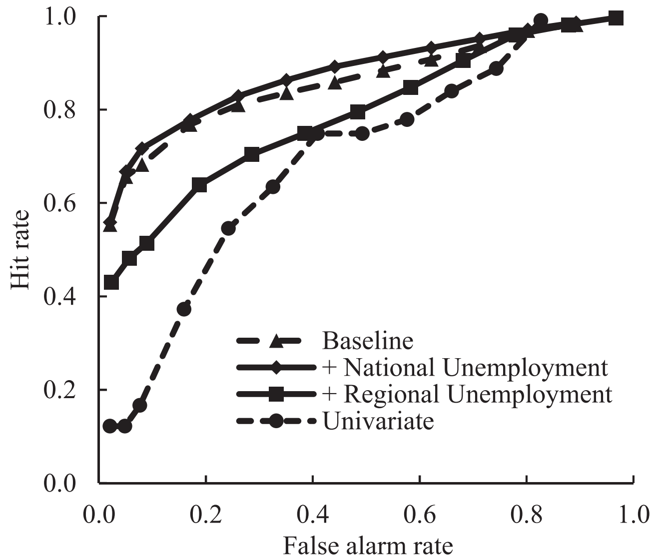
This section evaluates the out-of-sample performance of the models discussed above. More complex models that use more variables to predict failure will by design perform relatively well in in-sample fitting. The more dimensions that are used to explain observed failures, the closer the models will get to replicating these failures. This need not be true out of sample. Indeed, there is a body of evidence that shows that relatively simple models can outperform complex models based on out-of-sample measures (e.g., Haldane and Madouros 2012; Aikman et al. 2014). An aim of this paper is to evaluate the out-of-sample performance of the more complex multivariate models set out above for early-warning use by credit union supervisors.

There is no obvious separate sample on which to evaluate our models discussed above. As such, we rely on data-splitting techniques to separate our single sample of data into two, leaving a "training" sample on which we estimate our model and a "testing" sample on which we evaluate our model's performance in predicting actual credit union failures. This procedure is analogous to how we intend the model to be used in the supervision of credit unions—estimating the model on historical data of past credit union characteristics and failures (analogous to our training sample) and then using the estimated model to rank credit unions, based on their most recent regulatory data, according to their likelihood of failure. All else equal, a model that accurately classifies failure in our testing sample should perform well in predicting the failure of credit unions currently under supervision.

We begin the procedure by randomly selecting a subset of 400 of the roughly 700 different credit unions in our sample. We estimate four separate and distinct models on this training sample: (i) a simple univariate model based on asset size, (ii) our baseline model discussed above that includes only CAMEL covariates, (iii) our baseline model augmented with national unemployment measures, and (iv) our baseline model augmented with regional unemployment measures. We then fix model parameter estimates, and use these to calculate predicted probabilities of default for each of the firms in the testing, or holdout, sample. We define an "at risk" subsample of holdout firms who have a probability of default greater than some predetermined threshold. We use this subsample to calculate "hit rates" and false alarm (type II error) rates for each of the four models. By varying the threshold above which firms are designated at risk, we trace out ROC curves for each of our models. To minimize sampling error, we repeat this process 1,000 times and calculate average ROC curves.

Figure 5 shows out-of-sample testing results for our baseline model. It shows that the univariate model is clearly outperformed by

Figure 5. Out-of-Sample Performance: One-Year Model



Sources: Bank of England and authors' calculations.

each of the multivariate models. The one-year model with regional unemployment performs worse than the other multivariate models, suggesting that for near-term forecasts, regional unemployment may (somewhat surprisingly) degrade model performance and its use for supervisory purposes. The baseline model without regional unemployment performs better but is narrowly outperformed by the model with national unemployment. This is consistent with our in-sample findings discussed earlier where the inclusion of national unemployment is a highly significant factor in characterizing default in the upcoming year.

6. Conclusions

This paper develops an early-warning model for characterizing individual credit union failure in the United Kingdom based on firm-level and macroeconomic indicators of vulnerability. We define failure as the case where a credit institution was referred to the FSCS for depositor payout as part of a formal administrative process. The results show that a small set of firm-level financial CAMEL measures, including a simple non-risk-based capital ratio, asset arrears rates, unsecured loans, return on assets as well as liquid assets, and loan-to-deposit ratios is effective in characterizing potentially troubled credit unions one year in advance of failure. We also find that controlling for regional and national macroeconomic conditions improves in-sample classification and out-of-sample predictive ability.

As credit unions increase in prominence for households that may not have access to traditional forms of finance, understanding what leads to the failure of these institutions will become of increased importance. We believe our paper's results could be of value to supervisors tasked with ensuring the safety and soundness of individual firms and in identifying emerging threats to firm failure. Knowing which firms, and the extent to which the credit union sector overall, exhibit features similar to those that failed previously could help in allocating scarce supervisory resources and in curbing the effects of credit union failures on depositors and the regional economy. This information may also be of interest to the U.K. FSCS and provide benchmark criteria for establishing risk-sensitive levies supporting this compensation scheme.

For macroprudential purposes, the results may give policymakers at least an initial sense of sector resilience. For instance, there may be concerns when the results show a significant proportion of credit unions with high failure probabilities. Aggregating estimated failure probabilities across firms (e.g., on a simple or asset-weighted average basis) and monitoring these over time may also help reveal incipient risks within the sector. Monitoring how the distribution of failure probabilities evolves over time can also shed light on emerging trends and issues that may be of concern to supervisors.

Appendix

Table 9. Correlation Matrix

	Variable	1	2	3	4	5	6	7
1	Size	1.0000						
2	Capital Ratio	0.1370*	1.0000					
3	Arrears 3–12 Months	−0.1014*	−0.0182	1.0000				
4	Arrears > 12 Months	−0.0899*	−0.0554*	0.3376*	1.0000			
5	Provision Coverage	0.0950*	0.0094	−0.2174*	−0.1557*	1.0000		
6	Unsecured Loans	0.2839*	−0.0079	0.0493*	0.0283*	0.0059	1.0000	
7	Admin. Expense	−0.1701*	−0.0429*	0.0490*	−0.0633*	−0.0398*	−0.0396*	1.0000
8	Cost to Income	−0.2404*	−0.2433*	0.1865*	0.1692*	−0.1117*	0.0727*	0.2670*
9	ROA	0.1094*	0.3061*	−0.1536*	−0.1614*	0.0787*	−0.0512*	−0.0981*
10	Loans to Deposits	0.1833*	0.0770*	0.1332*	0.0478*	−0.0045	0.7192*	0.0506*
11	Liquidity Ratio	−0.2743*	0.2685*	−0.0091	0.0616*	−0.0274*	−0.3440*	0.0853*
12	Members	0.0194	0.0694*	0.0251*	0.0201	−0.0278*	0.0453*	0.0882*
13	Full-Time Staff	0.1513*	0.0240*	−0.0251*	−0.0216*	0.0229*	0.0246*	−0.0148

	Variable	8	9	10	11	12	13	
8	Cost to Income	1.0000						
9	ROA	−0.8163*	1.0000					
10	Loans to Deposits	0.1028*	−0.0265*	1.0000				
11	Liquidity Ratio	0.0185	0.0194	−0.2824*	1.0000			
12	Members	0.1117*	−0.1122*	0.0396*	0.0615*	1.0000		
13	Full-Time Staff	−0.0284*	0.0136	0.0266*	−0.0330*	0.0050	1.0000	

Source: Bank of England regulatory data and authors' calculations.
* indicates significance at the 0.10 level.

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