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The determinants of credit union failure in the United Kingdom: how important are macroeconomic factors?

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The determinants of credit union failure in the United Kingdom: how important are macroeconomic factors?

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Abstract

Using regulatory data on credit unions, this paper provides empirical evidence on the determinants of credit union failure in the United Kingdom. We find that a small set of financial attributes related to capital adequacy, asset quality, earnings performance and liquidity is useful for early identification of troubled credit unions. In and out-of-sample results indicate that this parsimonious set of firm-level characteristics, augmented with national and regional unemployment rates, reliably identifies failures while keeping false alarm rates at modest levels. The results provide support for establishing early warning criteria for supervisory use in monitoring credit unions.

Key words: Credit unions, failure, early-warning, logit, policymaker loss function.

JEL classification: G21, G28, G38.

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1. Introduction

Academic research on early-warning of bank failure is relatively widespread and typically shows that firm-specific and economic factors are important determinants of failure. Indeed, the large number of failures that occurred in the US 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., Dermiguc-Kunt, 1989; Whalen, 1991; Cole et al., 1995; Cole and Gunther, 1995; Wheelcock and Wilson, 1995, 2000; Sahajwala and Van den Bergh, 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).

Studies examining the drivers of credit union failure, however, are more limited and US specific. This narrow view is due, in part, to the fact that outright failures of credit unions in other countries are relatively rare. Rather than let credit unions fail, most jurisdictions have tended to transfer troubled credit unions' engagements to other healthier credit unions (e.g., McKillop et al., 2011; Jones, 2010). Smith and Woodbury (2010) also suggest that credit unions are less exposed to fluctuations in the business cycle, thus making them better able to withstand shocks to their balance sheets, which may help explain the bias towards more studies of bank failure. In the US, 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).[1]

Using regulatory data on credit unions in the United Kingdom, this paper contributes to the literature on early-warning systems and risk-profiling of credit unions. Specifically, we investigate the drivers of failure in the UK credit union sector which, to our knowledge, has not been examined before. Our paper adopts the framework employed in many of the aforementioned studies to evaluate the determinants of failure in the UK credit union sector.

[1] 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 US.

Using CAMEL factors (**C**apital adequacy, **A**sset quality, **M**anagement, **E**arnings performance and Liquidity) from the bank failure literature, we examine the characteristics of credit unions that failed between 2003 and 2015. Recent studies evaluating the determinants of distress in institutions with mutual ownership structures like that of the credit unions evaluated in this paper employ similar techniques and find that such CAMEL factors are helpful in characterizing distress in these firms (Fiordelisi and Mare, 2013; Mare, 2015; Francis, 2014). We extend these analyses to consider recent work on policymaker preferences (i.e., relative aversion with respect to missed 'failures' and 'false alarms') to help in evaluating the performance of our failure model. We are unaware of any other study that has specifically looked at this issue for credit unions. This perspective adds to the early-warning and risk-profiling research.

Credit unions face constraints related to lending and funding sources that could possibly affect the way in which sources of failure in the banking sector play out in the credit union sector. In particular, legal restrictions around the setup of credit unions mean that they are more dependent on depositors and are exposed to borrowers with common characteristics (e.g., region, industry, job type, employer). These common attributes could make it relatively more difficult for them to diversify funding and credit risks compared with banks. A key contribution of this paper is to examine if such constraints affect the sources and likelihood of failure differently in the credit union sector. While our analysis focusses on the UK, it is relevant for other countries that have a sizable credit union, such as Canada where 1 in 5 Canadians belong to a credit union and have borrowed almost CAD$160 billion in loans.[2]

Despite playing a narrower role than traditional banking institutions in providing credit and transactional deposit services, UK credit unions remain firmly on the radar of prudential supervisors given the important role they play in supporting local economies.[3] They do this mainly by supplying credit to consumers that typically find it difficult to obtain credit from

[2] See https://www.ccua.com/credit_unions_in_canada/credit_unions_lead_the_way .
[3] The Bank of England's Prudential Regulation Authority (PRA) supervises roughly 500 credit unions with close to 2 million members and £3 billion assets. Monitoring the health of individual credit unions and the sector overall is part of the PRA's overall remit, and consistent with its primary safety and soundness and secondary competition objectives.

traditional banks or building societies in the UK, thus filling gaps in the credit supply channel and fostering economic activity that might otherwise go unfunded (Jones, 2016). In addition, the UK credit union sector continues to garner attention in light of government efforts to widen financial inclusion and promote effective competition in the UK banking sector (e.g., see Hope, 2010; Jones, 2016). These features help explain why having a sound, fundamental understanding of the characteristics of potentially troubled credit unions is crucial for effective monitoring and supervisory oversight of these institutions.

Our paper develops this understanding further by examining the financial characteristics of failed credit unions one, two and three years prior to their demise. To define and date credit union failure, we use a dataset on institutions that have been referred to the UK Financial Services Compensation Scheme (FSCS) for depositor pay-out as part of the formal administration process.[4] We combine this information with annual regulatory reporting 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 dataset with several macroeconomic variables, both at the national and regional levels, which allow us to test the effects of such factors on 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, become increasingly more important for characterizing failure in the longer-horizon. Out-of-sample performance results indicate that this parsimonious set of firm-level characteristics, along with unemployment measures, classifies

[4] 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.

failures reliably while keeping false-positive (Type II) error rates at modest levels. Overall, these results highlight the significance of other sources of credit union 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 UK credit union sector. Section 3 describes our dataset, empirical approach and framework for evaluating model performance. Section 4 discusses results, while section 5 reviews model performance. Section 6 concludes.

2. Background on UK credit unions[5]

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 loans, although some also provide mortgage products and other ancillary services such as basic bank accounts or cash Individual Savings Accounts (ISAs).

Credit unions are not subject to the same market pressures for growth and earnings performance as for-profit financial institutions. Nevertheless, they still face pressures from regulatory requirements to maintain minimum levels of capital and liquidity.[6] If a credit union breaches such minima, they are required to undertake corrective actions or can be subject to more supervisory intervention, including closure.

[5] For more extensive overviews, see McKillop et al. (2010) and Jones (2016).

[6] For example, during the period covered by our study small credit unions (with less than 5,000 members and assets under £5 million) were required to maintain capital of at least 3% of total assets. This increased to 5% for medium-sized institutions (with members from 5,000 to 10,000 and with assets of between £5 and £10 million). All other credit unions were subject to a capital requirement of 8% risk-adjusted capital to total asset requirement, where risk-adjusted capital equalled capital plus provision for bad and doubtful debt less the minimum specific provision for bad and doubtful debt. Credit unions were required to hold a liquidity ratio of at least 10% at all times.

3. Data and empirical approach

We use annual data (spanning 2002 to 2015) from credit unions' regulatory submissions to the UK Financial Services Authority (FSA) (from 2002 to 2013) and Prudential Regulation Authority (PRA) (since 2013). All credit unions supervised by the FSA and PRA are required to submit detailed breakdowns of their assets and liabilities, profit and loss, solvency and liquidity positions. The dataset 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 how the number of credit unions in our sample evolved over time. From 2002 to 2012, the number of such institutions in Great Britain from declined from almost 600 to under 400 due, in large part, to the transfer of engagements to other credit unions and, to a lesser extent, several failures (defined below). The number of credit unions jumped to over 500 in 2012 as the scope of the UK 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 UK-supervised credit unions increased five-fold from less than £0.5 billion in 2002 to over £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 pay-out. From 2002 to 2015, there were 85 such failures, although only 68 are included in our dataset due to a lack of corresponding regulatory return information for 17 institutions. Table 1 reports the annual failure rates for our sample period. For the period 2003 to 2015, the failure rate averaged around 1 percent, but varied considerably over time, peaking in the two years in the immediate aftermath of the crisis. We also find that no one region stood out as contributing disproportionately to firm failure.[7]

[7] Across the thirteen regions in the UK, the distribution of failures was as follows:

	NA	GL	EM	East	NE	NW	NI	SC	SE	SW	Wales	WM	Y&H	Total
	9	5	5	2	5	7	1	7	2	6	4	9	6	68
% Total	13%	7%	7%	3%	7%	10%	1%	10%	3%	9%	6%	13%	9%	100%

3.1 Explanatory variables

Following the literature on the drivers of bank failure, we construct several measures of financial condition and performance. We start with determinants related to capital adequacy, asset quality, managerial skills, earnings and liquidity, or the CAMEL characteristics, typically used in characterizing financial soundness. We then introduce other potential determinants relating to the macroeconomic environment.[8]

Table 2 summarizes our candidate CAMEL variables and the expected association with failure. To gauge capital adequacy, we include a simple capital ratio and a risk-adjusted capital ratio. The simple ratio – equal to total capital as a percentage of total assets – is analogous to a 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. The risk-adjusted ratio, which adjusts total capital for net excess provisions, has the same intuition, but is only calculated by the largest version 1 and all version 2 credit unions.[9] We expect both metrics to be negatively associated with 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 3 and 12 months in arrears and another based on loans over 12 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 as a proxy for credit risk exposure overall. A higher ratio suggests relatively greater credit risk. We expect these three proxies for asset quality to be

Notes: NA = Not assigned; GL = Greater London; EM = East Midlands; East = Eastern England; NW = North West; NI = Northern Ireland; SC = Scotland; SE = South East; SW = South West; WM = West Midlands; Y&H = Yorkshire and the Humber.

[8] Appendix 1 provides full details on all variables in our dataset and their underlying sources.

[9] Version 2 credit unions were, in general, relatively larger in size and had less restrictive borrowing, lending and investment limits. Categorization as a version 2 credit union required the credit union to demonstrate requisite financial and management capabilities to engage in relatively more complex business.

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 metrics related to credit union membership (i.e., number of members) and 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 the 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 Appendix 1) 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 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, a higher ratio means more reliance on wholesale funding, which, because of its volatile nature, can be more sensitive to firm-level and economic conditions, leading to increased chances of a funding shock and, in turn, credit union failure.

3.2 Descriptive statistics

Table 3 reports summary statistics on our CAMEL variables.[10] This table also includes some additional variables related to credit unions' reliance on subordinated debt funding, as well as macroeconomic control variables. As discussed below, we use these measures to evaluate the role that market discipline and economic conditions may play in influencing credit union risk-taking behaviour.

Table 4 reports mean equality tests between failures and survivors from a simple univariate analysis for our main candidate variables. The tests suggest that failed credit unions are generally smaller, less well capitalised, 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 (higher cost-to-income ratios) and weaker liquidity positions (higher loan-to-deposit ratios).

3.3 Modelling 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).[11] The probability of credit union failure over the next k (= 1 to 3) years is equal to:

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

[11] 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

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

where $Y_{i,t}$ is an indicator variable equal to one if credit union *i* fails (i.e., if it gets referred to the FSCS for pay-out) in year *t* and equal to zero if the credit union remains active. The term in the denominator on the right-hand side, $\sum_{j=1}^{J} \beta_j X_{i,j,t-k}$, represents a linear combination of our *j* explanatory variables, which, discussed below, includes CAMEL and macroeconomic factors.

In the above equation, the sign of the beta coefficient denotes the direction of the influence of a marginal change in the corresponding explanatory variable on the probability of failure. Unlike under a standard OLS framework, the marginal impacts of each explanatory variable cannot be interpreted by looking only at the coefficients. Rather, the magnitude of the impact depends on the values of all the other explanatory variables and their coefficients.

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.

This equation helps determine the factors that characterize failure *k* years prior to the actual failure event. 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. The distance the variables are lagged is equivalent to the length of the forecast period. So, for example, a 1-year (2-year) lag means that the financial variables predict the likely failure one year (two years) hence. In what follows, we examine the classification performance of several models using lags of one, two and three years.

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explaining US commercial bank failures during the banking crisis of the late 1980s and early 1990s.

3.4 Evaluating model performance for supervisory use

We follow Alessi and Detken (2011) to set out a framework for assessing model performance. Under this approach, we consider that a supervisor has a relative preference between a Type I error (i.e., misclassifying a failure) and a Type II error (i.e., misclassifying a healthy firm as a failure). Here, we implicitly assume that when setting preferences, supervisors consider the expected costs that arise from the failure of a credit union and from issuing a false alarm about a healthy institution.

To evaluate our failure models and the potential trade-offs in the context of early-warning systems, we rely on the standard Type I versus Type II error trade-off approach used in the banking literature (e.g., Poghosyan and Cihak, 2011; Betz et al., 2013; Aikman et al., 2014) and concepts from Alessi and Detken (2011). The basic idea is to choose a threshold probability, $\pi \in [0, 1]$, above which our models issue 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-k, $p_{i,t\text{-}k}$, into another binary variable $F_{i,t\text{-}k}$ that equals one if $p_{i,t\text{-}k}$ exceeds π and zero otherwise. The association between the forecast (signal) $F_{i,t\text{-}k}$ and the actual failure, as represented by $Y_{i,t}$, can be summarized using a classification matrix as set out below.

Signal issued at time t-k?	Forecasted Event $F_{i,t\text{-}k}$	Actual Failure Event $Y_{i,t}$ Failure	Actual Failure Event $Y_{i,t}$ Non-failure
Yes ($F_{i,t\text{-}k}$ = 1)	Failure	True Positive (TP)	False Positive (FP)
No ($F_{i,t\text{-}k}$ = 0)	Non-failure	False Negative (FN)	True Negative (TN)

Here we focus on the elements of the classification matrix that may be of most concern to supervisors: missing credit union failures (i.e., False Negatives, or Type I errors) and issuing false alarms on viable credit unions (i.e., False Positives, or Type II errors). We do not attempt to quantify the costs associated with each error in this paper, but rather we follow Alessi and Detken (2011) to transform supervisors' preferences into a loss function, where supervisors have a relative preference between Type I and II errors. A Type I error occurs when the 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 $T_2 = FP/(FP+TN)$. Given the model-derived probabilities p, the supervisor should choose a threshold π such that loss is minimized. A supervisor's loss consists of T_1 and T_2, weighted according to relative preferences between missing failures, θ, and issuing false alarms, $1-\theta$. We can express the supervisor's loss function as follows:

$$L(\theta) = \theta T_1 + (1-\theta) T_2 \,, \tag{2}$$

where $\theta \in [0,1]$ is the supervisor's relative risk aversion between Type I and Type II errors and T_1 and T_2 denote Type I and Type II errors, respectively. In other words, this loss function represents the preference weighted sum of Type I and Type II errors. A θ lower than 0.5 reveals that the supervisor is less averse towards missing a signal for a credit union failure compared with receiving a false alarm about a healthy credit union.

Another way to assess model performance is to use measures from receiver operating characteristic (ROC) curves and the area under the ROC curve. 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:

$$ROC = \frac{PR\left(Y_{i,t} = 1 \middle| F_{i,t-k} = 1\right)}{1 - PR\left(Y_{i,t} = 0 \middle| F_{i,t-k} = 0\right)}, \tag{3}$$

where $Y_{i,,t}$ and $F_{i,t-k}$ are as defined above. In this regard, the ROC curve shows the trade-off 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.

4. Results

To help establish our baseline results, we ran a series of specifications involving several combinations of the variables in our dataset. Table 5 presents the results of our preferred baseline 1-, 2- and 3-year models. Model 1 is conditioned on financial data reported in credit unions' annual regulatory returns in the year immediately prior to the year in which an FSCS referral event occurred. For early-warning purposes, this model provides an estimate of the likelihood of failure in the upcoming year. Models 2 and 3 have similar interpretations, but are aimed at estimating failure likelihood two and three years into the future.

Each of our baseline models includes at least one of the CAMEL factors. The results also suggest that a small set of such measures is useful for characterizing potential failures. In addition, the signs on all coefficient estimates are in line with expectations across all three models. Asset size, capitalization and earnings are negatively associated with the probability of failure, which accords with findings from bank failure research (e.g., see Cole et al., 1995; Cole and Wu, 2009; Poghosyan and Cihak, 2011).[12] These results suggest that small credit unions with low capital ratios and weak earnings are more likely to fail within the upcoming three years. The positive signs on arrears rates and the proportion of unsecured loans (for Model 2) imply that the likelihood of failure increases as asset quality deteriorates.

Column 3 shows that the liquidity ratio is only significant in the 3-year model. It is negatively correlated with the probability of failure, indicating that a credit union with less liquid assets available to meet immediate outflows has a higher likelihood of failure in three years. Our second liquidity measure, the loan-to-deposit ratio, is positive and statistically significant in the 2-year model (column 2). This finding supports the idea that firms with greater reliance on non-retail deposit funding are more likely to fail in two years' time.

Our pseudo R-square for the 1-year model is 0.35, which is high compared with the fit of similar models in the bank failure literature (e.g. see Anoniades, 2015; Cole and White, 2009; De Young and Torna, 2012). However, the area under the ROC shows that correctly classifying failures and survivors diminishes as the forecast horizon increases. Overall, the results suggest CAMEL factors are useful in characterizing failures, especially in the short-run.

[12] 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 three years. We excluded this variable from our baseline specifications due to the high correlation (see Appendix 2) with our earnings measure, roa, to mitigate issues with multicollinearity.

4.1 Robustness checks

To assess the reliability of our 1-, 2- and 3-year baseline models we undertook several robustness checks. Table 6 reports results of these tests. In general, our results are robust to region and year fixed effects as well as exclusion of larger version 2 credit unions.

As discussed above, charter restrictions limit the extent to which credit unions can diversify across geographic location, which potentially makes them vulnerable to local regional conditions. This restriction may also mean that failure might depend on shocks experienced in the region in which a credit union is located. To account for this possibility, we include regional dummy variables in our estimations (columns 1, 5 and 9 in Table 6).[13] While not reported, almost all regional dummies were not statistically significant in explaining credit union failure. In addition, the signs and statistical significance on the variables in our baseline 1-, 2- and 3-year models remain unchanged, demonstrating the robustness of our results to the inclusion of regional effects.

As a second check, we consider the chance that credit union failure is influenced by common shocks affecting credit unions simultaneously. To account for such common shocks, we include time dummy variables (year effects) in estimates (reported in columns 2, 6 and 10 Table 6). The results show that the qualitative findings with regards to our baseline models remain unchanged. The signs and significance levels on each variable are similar when accounting for year effects, further supporting the robustness of our baseline estimations.

As a third check, we incorporated both regional and year effects in our analysis. The results (reported in column 3, 7 and 11 Table 6) again confirm the robustness of the baseline model variables. The signs and significance levels on our baseline variable are similar even after accounting for region and year effects together.

Finally, we evaluate the degree to which our results might be affected by the inclusion of version 2 credit unions. Such institutions, of which there were only 2 failures over our

[13] We segregated the UK into 12 distinct regions and assigned credit unions to those regions based on post codes reported on the annual regulatory return (see Appendix 1).

estimation period are larger both in size and membership. Version 2 credit unions are, in general, also subject to more stringent capital requirements and more intensive supervisory scrutiny. To check whether these different features matter to our results, we estimated the baseline models using only version 1 credit unions (columns 4, 8 and 12 of Table 6), which make up three-quarters of our observations and over 90 percent of the failures. The results suggest that for each of our baseline 1-, 2- and 3-year models, the results are not materially influenced by the inclusion of version 2 institutions, as all qualitative findings remain unchanged.

4.2 Additional tests

Previous literature shows that macroeconomic conditions may be important drivers of banking crises (e.g., see Beck et al., 2006; Cihak and Schaeck, 2007) and individual bank failures (e.g., De Young and Torna, 2012). Lower rates of unemployment and inflation, 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 inflation and the regional and local unemployment rates as additional controls. We also include controls for whether a credit union relies on uninsured, subordinated debt to support its operations, as prior research suggests that such funding exerts market discipline on the risk-taking behaviour of banks (e.g., Flannery and Nikolova, 2004 and Covitz, et al., 2004).

Table 7 reports the results of including these additional controls in the 1-, 2- and 3-year baseline models. Columns 1, 5 and 9 of the table show that lagged national unemployment rate is positively correlated with failure. Indeed, the inclusion of national unemployment improves the in-sample fit of each baseline model as suggested by the increase in pseudo R-squared measures and the area under the ROC curve.

Credit union failure may also be sensitive to regional indicators, given the lack of diversification of its membership. Columns 2, 6 and 10 of Table 7 show that regional unemployment is positively associated with failure. The results also indicate that the fit of the 2-

and 3-year models improves little with the inclusion of national versus regional unemployment. This may be because the national unemployment rate has more pervasive effects on the economy, for example by affecting interest rates. It could also be due to the fact that a number of credit unions' common bond is not region-specific, but based on a common industry or social group.[14]

We also find that inflation (measured by the consumer price index or CPI) is also positively correlated with probability of failure, but only in the 2- and 3- year horizons.[15] This may be because inflationary effects take time to filter through to borrowers' payment capacity.

Finally, we included the share of total assets supported by uninsured subordinated debt funding to test for market discipline. The uninsured nature of such funding may provide a source of market discipline on credit unions' risk-taking behaviour that could, in turn, influence our estimates of the probability of failure. If this is the case for credit unions, then we might expect to find a negative association between subordinated debt and failure. Nevertheless, these disciplining effects could also depend on the stability of such funding. Relatively longer tenor funding may be less effective as a disciplining tool since it is not vulnerable to sudden withdrawal in response to an (ex post) shift in an issuer's risk profile. For this reason, we divide the share of subordinated debt funding into short- (maturities than four years) and long- term (maturities exceeding 4 years). The results of our analysis suggest little evidence of market disciplining effects.

Looking across Table 7, one can see that the signs and significance of our main variables in the 1-, 2- and 3-year models remain broadly unchanged regardless of the addition of control variables. One notable exception is when including national unemployment in the 1-year model

[14] Comparisons of AIC and 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.
[15] We also found that the baseline results are robust to the inclusion of lagged changes in GDP. The unreported results show a negative association between failure and GDP growth, suggesting that as economic output improves (worsens), the likelihood of failure decreases (increases). Results are available upon request.

(column 1), where we find that size can explain failure. Overall, however, the qualitatively similar results across all specifications provide further indication of the robustness of our baseline results.

4.3 Economic significance

The coefficients of the baseline logistic models 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 (e.g., see Verbeek, 2005). 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 1-, 2- and 3-year models, supplemented with national unemployment rates. 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 size and national unemployment rates have material influences on the likelihood of credit union failure across all three models. For the 1-year model, capitalization, arrears rates and liquid assets feature notably in explaining near-term failure. With respect to the 2- and 3-year models, the economic significance of capitalization continues, while the proportion of unsecured loans is relatively more important in explaining failure over longer horizons. Liquidity measures also play large roles in explaining failures over the longer-term, though the positive (albeit not statistically significant) association with the liquidity ratio in the 2-year model stands out. This finding may suggest that inefficiencies in balance sheet and net interest margin management could signal potential troubles and that that supervisors may want to consider the liquidity ratio alongside managements' balance sheet strategies when evaluating this measure as an early-warning tool.

As another way of illustrating economic significance, we report the marginal impacts separately for each the CAMEL covariates and the national unemployment rate found significant in our augmented baseline models (see Appendix 3). Each figure 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, earnings performance and unsecured loan proportions (particularly in the 2- and 3-year models). These figures again illustrate the pronounced effects of unemployment and the importance of considering economic conditions for early identification of at risk credit unions.

5. Model performance

This section reviews the ability of our estimated baseline models 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 Tables 5, 6 and 7 indicate that, while the baseline 1-, 2- and 3-year models have relatively high discriminatory power, performance improves with the addition of unemployment rates. In particular, the area under the ROC curve for the baseline 1-year model is roughly 90% and increases to 92% when augmented with national unemployment rates.[16] The area under the ROC curve for the baseline 2-year model increases from 83% to 87% when supplemented with regional unemployment measures. For the 3-year model, the area under the ROC curve increases from 82% to 87% (88%) when augmented with national (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.

As discussed above, the choice of threshold for setting signals depends on policymakers' relative aversion to Type I and Type II errors and, more specifically, the costs associated with each. A higher threshold signals fewer credit union failures resulting in higher Type I errors. While these errors can be mitigated by setting a lower threshold, doing so comes at the expense of generating more Type II errors. The optimal threshold will ultimately depend on the relative risk aversion of supervisors towards Type I and Type II errors. From a prudential perspective, there may be compelling reasons for placing more weight on Type I errors, since that could help avoid missing vulnerable credit unions and reduce costs associated with such cases.[17] On the other hand, placing too much weight on avoiding Type I errors can be pose significant supervisory resource costs and be unduly burdensome on regulated credit unions.

5.2. Out-of-sample forecasting performance

This section evaluates the out-of-sample performance of more complex early-warning models such as that 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

[16] Somewhat surprisingly, the area under the ROC curve for the 1-year model falls to 85% with the inclusion of regional unemployment measures (see Table 7, column 2).
[17] In the banking sector, these costs could include losses to the real economy that could arise from, for example, the reduction in critical lending and payment services.

used to explain observed failures, the closer to replicating these failures the models will get. This need not be true out-of-sample. Indeed, there is a body of evidence that shows relatively simple models can outperform complex models based on out-of-sample measures (e.g., Haldane and Madouros, 2012; Aikman et al., 2014). A key aim of this paper is to evaluate the out-of-sample performance of a more complex model such as the one 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 – estimated on historical data of past credit union characteristics and failures (analogous to our training sample) and then use the parameters from such a model to rank credit unions, based on their most recent regulatory, according to the 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 minimise sampling error we repeat this process 1,000 times, and calculate average ROC curves.

Figures 4, 5 and 6 show out-of-sample testing results for our 1-, 2- and 3-year models, respectively. For the 1-year model, the univariate model is clearly outperformed by each of the multivariate models. The 1-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 in discussed earlier where the inclusion of national unemployment is a highly significant factor in characterizing of default in the upcoming year.

Figure 5 shows model performance for the 2-year specification, while Figure 6 shows how the 3-year model performs. The relative out-of-sample performance of each of these longer-horizon models is broadly the same as in the 1-year model, with the exception of the model including regional unemployment, which performs better for forecasting longer-term failure. Thus, while regional unemployment does not help forecast imminent credit union default, it appears relatively more useful in predicting default in the medium term. Figure 7, which shows the ROC curves for the baseline model at the 1-, 2- and 3-year time horizon, confirms that as we extend the time horizon over which we predict failure, model performance declines: for a given hit rate we have to accept a higher false alarm rate at longer horizons.

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 whether the credit institution was referred to the FSCS for depositor pay-out 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, two and three years in advance of failure. We also find that controlling for regional and national macroeconomic conditions improves the in-sample classification and out-of-sample predictive ability of our 1-, 2 and 3-year models.

As credit unions increase in prominence for households who 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 potentially in curbing the effects of credit union failures on depositors and the regional economy. Such output may also be of interest to regulation of the UK FSCS and provide benchmark criteria for establishing risk-sensitive levies supporting this compensation scheme.

Supervisors may also find the information from these reduced-form models helpful in informing judgments about firm-specific risks and broader sector risks, by using a regression approach to inform their qualitative assessments. Because the output of the multivariate regression models represents a summary statistic of firm-level vulnerability based on several measures derived from routinely filed regulatory returns, it is possible to update such summary statistics on a regular basis as these data are collected. Our models can help rank credit unions according to their likelihood of failure, and these rankings can help inform decisions about how to focus on-site and off-site reviews, as well as in directing scarce supervisory resources.

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.

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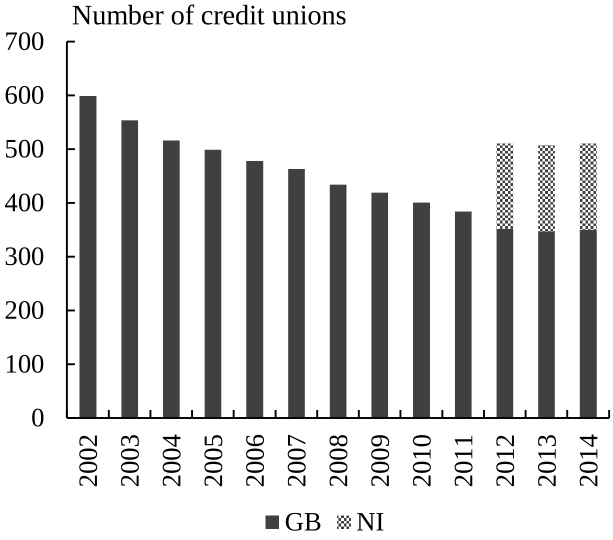
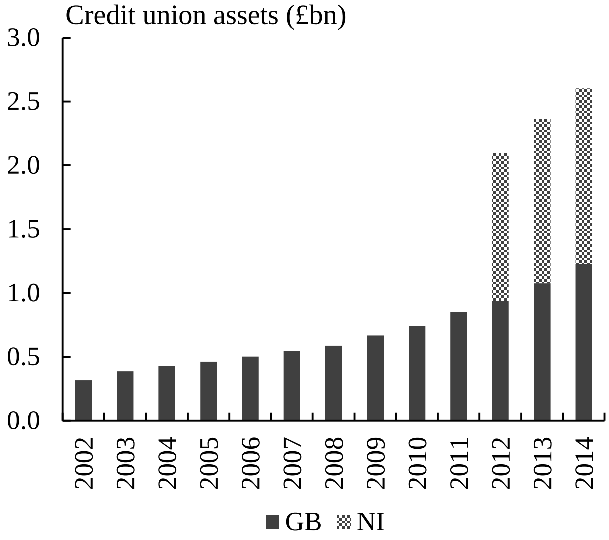
Figure 1: Number of credit unions



Source: Bank of England.

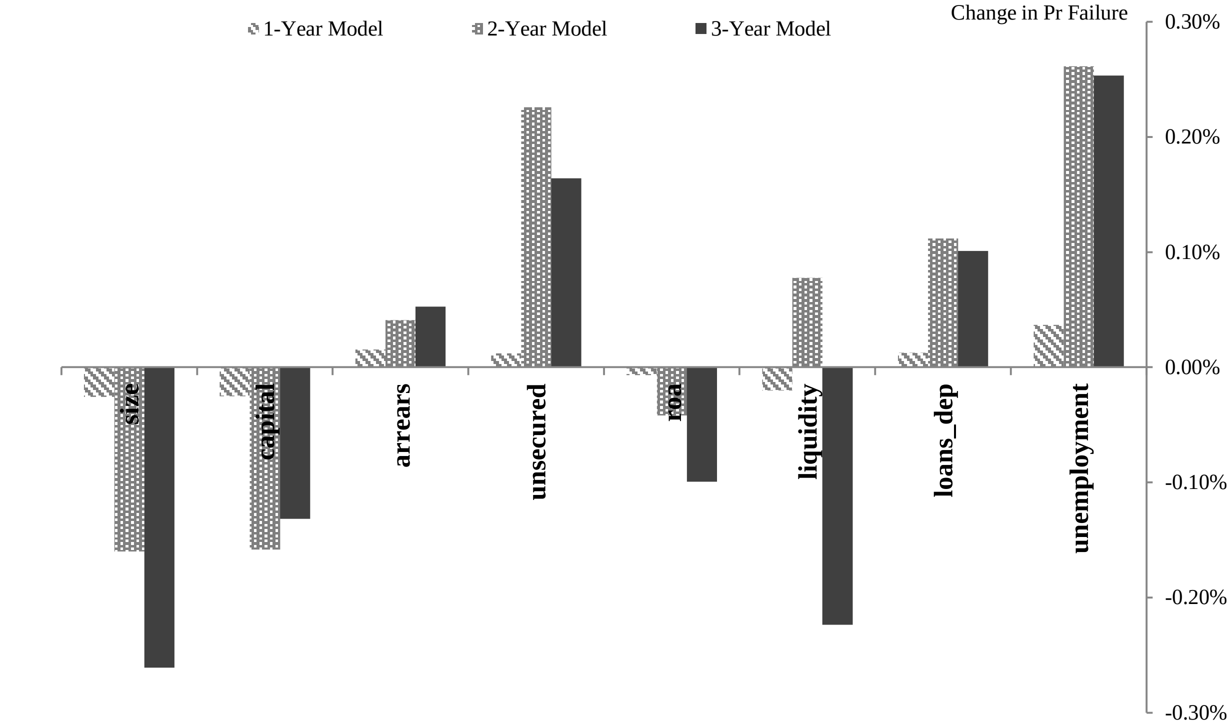
Figure 2: Size of the UK credit union sector



Source: Bank of England.

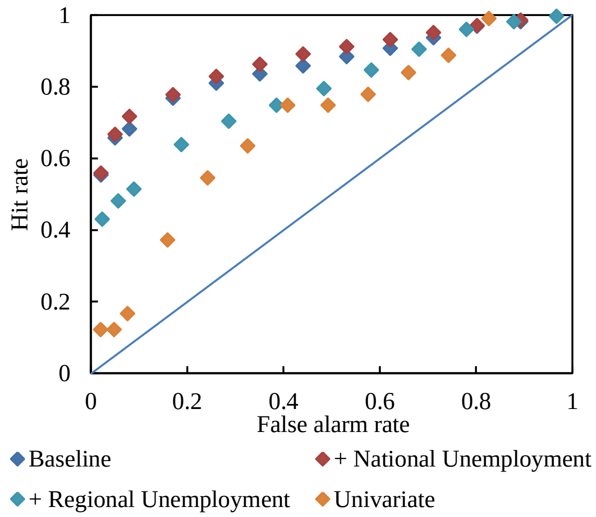
Figure 3

Effect of one standard deviation change in each variable on failure probability



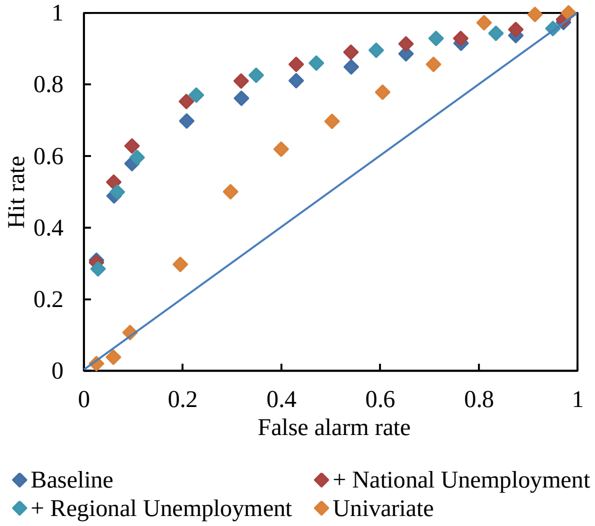
Source: Authors' calculations.

Figure 4 Out-of-sample performance: 1 year model



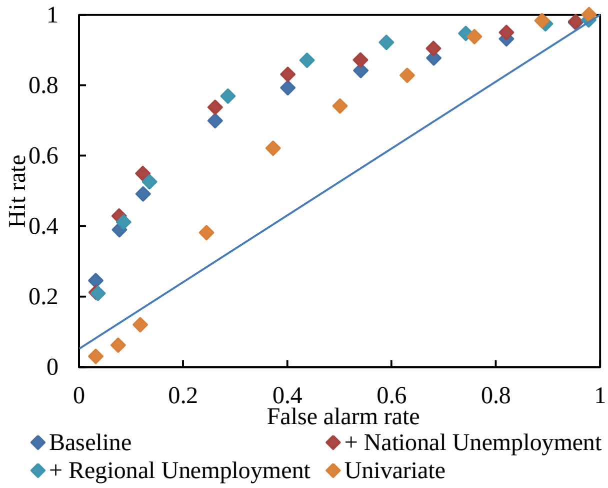
Source: Bank of England and authors' calculations

Figure 5 Out-of-sample performance: 2 year model



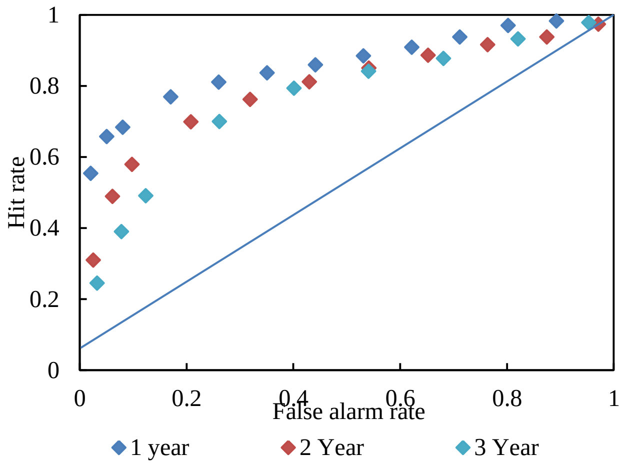
Source: Bank of England and authors' calculations

Figure 6 Out-of-sample performance: 3 year model



Source: Bank of England and authors' calculations

Figure 7 Out-of-sample performance: baseline model through time



Source: Bank of England and authors' calculations

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	6592	68	1.03%

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

Table 2
CAMEL predictors of failure

CAMEL factor	Definition[(a)]	Expected Association with failure
Capital Adequacy:		
simple capital ratio	Total Capital/Total Assets	-
adjusted capital ratio	Total Risk-adjusted Capital/Total Assets[(b)]	-
Asset Quality:		
total arrears	Net Liabilities in Arrears/Total Net Liabilities[(c)]	+
arrears 3-12 months	Net Liabilities 3-12 months in Arrears/Total Net Liabilities	+
arrears > 12 months	Net Liabilities > 12 months in Arrears/Total Net Liabilities	+
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[(d)]/Total Relevant Liabilities[(e)]	+/-
loans to deposits	Total Loans/Total Members' Share Balance	+

Notes: (a) Unless otherwise noted, all measures are expressed as percentages, and have been multiplied by 100; (b) total risk-adjusted capital is calculated for larger version 1 and version 2 credit unions and equals total capital plus the lesser of net provisions (i.e., total provisions less minimum specific provisions) or 1% of total assets; (c) net liabilities equal total loans plus accrued interest less the members' share balances used to secure the loan; (d) total liquid assets equals the sum of qualifying cash and bank balances, investments realizable within 8 days, unused committed facilities and unused overdrafts; (e) total relevant liabilities equal the sum of unattached shares and liabilities with an original or remaining maturity of less than three months.

Table 3
Summary statistics[(a)]

Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
size (log total assets)	6601	12.89	1.67	4.46	18.71
capital ratio (%)	6591	8.74	8.17	-11.36	48.01
adjusted capital ratio (%)	663	12.76	9.15	0.01	99.00
total arrears[(b)] (%)	5905	8.58	9.12	0.09	47.95
arrears 3-12 months[(b)] (%)	6448	9.65	14.33	0.00	97.24
arrears > 12 months[(b)] (%)	6486	7.49	14.24	0.00	85.71
provision coverage (%)	5557	179.16	297.13	36.28	2200.00
unsecured loans[(c)] (%)	6306	41.51	24.81	2.59	100.39
cost to income ratio (%)	6601	82.84	33.73	16.31	230.68
return on assets (%)	6601	1.61	3.47	-13.29	13.27
admin expense ratio (%)	6601	6.82	10.08	0.00	60.43
liquidity ratio (%)	6564	77.07	63.00	6.70	501.99
loans to deposit ratio	6560	68.56	28.35	10.93	159.83
long-term sub debt[(c)] (%)	6663	0.24	2.22	-1.15	95.71
short-term sub debt[(c)] (%)	6663	0.08	1.53	0.00	68.99
total sub debt[(c)] (%)	6663	0.24	2.19	0.00	86.24
Members	6578	1.76	13.49	0.00	1069.71
full-time staff	6601	2.92	9.87	0.00	663.00
national unemployment rate	6601	6.18	1.27	4.8	8.1
regional unemployment rate	6018	6.31	1.56	3.4	10.6

Source: Bank of England and authors' calculations.
Notes: (a) bank-level characteristics based on measures at the 1st and 99th percentiles; (b) percentage of total net loans to members; (c) percentage of total assets.

Table 4
Mean comparison tests

	Failures		Survivors		Mean Equality Test (t-test, unequal variances)	
Variable	**Mean**	**Obs**	**Mean**	**Obs**	**Difference**	**p-value**
Size (log of total assets)	11.88	421	12.96	6180	-1.08	0.00
capital ratio (%)	4.04	418	9.06	6173	-5.02	0.00
adjusted capital ratio (%)	7.25	13	12.87	650	-5.62	0.00
total arrears percent (%)	12.77	381	8.29	5524	4.48	0.00
arrears 3 to 12 months (%)	13.82	463	9.33	5985	4.49	0.00
arrears over 12 months (%)	10.57	466	7.25	6020	3.32	0.00
unsecured loan to assets (%)	11.03	336	7.59	5401	3.44	0.00
provision coverage (%)	50.93	399	40.87	5907	10.06	0.01
cost to income (%)	107.52	421	81.16	6180	26.36	0.00
return on assets (%)	-0.55	421	1.76	6180	-2.31	0.00
admin expense to assets (%)	11.87	421	6.48	6180	5.39	0.00
liquid asset ratio (%)	74.78	413	77.23	6151	-2.45	0.32
loans to deposits (%)	77.93	416	67.92	6144	10.01	0.00
sub debt ratio (%)	0.31	483	0.23	6180	0.08	0.58
long-term sub debt ratio (%)	0.15	483	0.08	6180	0.07	0.72
short-term sub debt ratio (%)	0.30	483	0.23	6180	0.07	0.32
membership (000's)	0.63	419	1.84	6159	-1.21	0.00
full-time staff size	3.22	421	2.90	6180	0.32	0.83

Source: Bank of England and authors' calculations.

Table 5
Baseline specifications at different forecasting horizons

	(1)		(2)		(3)	
Explanatory Variables	**Model 1 1-Year Baseline**		**Model 2 2-Year Baseline**		**Model 3 3-Year Baseline**	
size	-0.4795		-0.3027	**	-0.5101	***
	(0.3136)		(0.1535)		(0.1442)	
capital ratio	-0.1429	*	-0.0948	**	-0.0425	
	(0.0819)		(0.0390)		(0.0328)	
arrears > 12 months	0.0260	***	0.0141	**		
	(0.0080)		(0.0065)			
arrears 3-12 months					0.0088	*
					(0.0052)	
unsecured loans	0.0109		0.0218	***	0.0133	
	(0.0116)		(0.0072)		(0.0083)	
roa	-0.0664		-0.0682		-0.1010	**
	(0.0694)		(0.0417)		(0.0442)	
liquidity ratio	-0.0129		0.0035		-0.0122	**
	(0.0104)		(0.0032)		(0.0054)	
loan to deposit ratio	0.0078		0.0106	*	0.0081	
	(0.0084)		(0.0058)		(0.0079)	
constant	-0.2473		-2.8441	*	1.4122	
	(3.6714)		(1.6626)		(1.6544)	
Number of Observations	6117		5309		4557	
Wald Chi2	85.4837		132.1366		111.9796	
Probability > Chi2	0.0000		0.0000		0.0000	
Pseudo R2	0.3504		0.1778		0.1534	
Log Likelihood	-94.6888		-201.5120		-221.5856	
AIC	205.3776		419.0239		459.1712	
BIC	259.1282		471.6412		510.5666	
Area Under ROC Curve	0.9057		0.8364		0.8283	

This table reports results of the logistic regression model $\log[p_{i,t}/(1-p_{i,t})] = \beta_0 + \sum_{j=1}^{N} \beta_j X_{j,i,t-k} + \varepsilon_{i,t}$, 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 pay-out in year *t* given the vector of *j* explanatory variables at time *t-k*. Definitions of all explanatory variables are listed in Appendix 1. Standard errors are reported in parenthesis below their coefficient estimates and adjusted for both heteroskedasticity and within correlation clustered at the credit union level. The area under the receiver operator characteristic (ROC) curve is a measure of how well each specification can distinguish between failures survivors, with larger areas representing better performance. * (**) {***} indicates significance at the 0.10 (0.05) {0.01} level.

Table 6

1-, 2- and 3-year baseline models with region, year and sample effects

	1-Year Model				2-Year Model				3-Year Model			
Variables	**(1) Region**	**(2) Year**	**(3) Region & Year**	**(4) Version 1 Only**	**(5) Region**	**(6) Year**	**(7) Region & Year**	**(8) Version 1 Only**	**(9) Region**	**(10) Year**	**(11) Region & Year**	**(12) Version 1 Only**
size	-0.5585*	-0.9096***	-0.9676***	-0.5015	-0.2801*	-0.6966***	-0.6450***	-0.2580	-0.4771***	-0.7487***	-0.7073***	-0.474***
	(0.3163)	(0.2897)	(0.3600)	(0.3457)	(0.1545)	(0.1774)	(0.1883)	(0.1690)	(0.1430)	(0.1526)	(0.1571)	(0.1565)
capital ratio	-0.1546	-0.1774*	-0.1725*	-0.1464*	-0.0875**	-0.1098***	-0.1064**	-0.0940**	-0.0344	-0.0524*	-0.0453	-0.0414
	(0.0981)	(0.0905)	(0.0903)	(0.0887)	(0.0432)	(0.0358)	(0.0419)	(0.0408)	(0.0297)	(0.0314)	(0.0304)	(0.0338)
arrears > 12 months	0.0246***	0.0270***	0.0275***	0.0273***	0.0098	0.0104*	0.0078	0.0142**				
	(0.0091)	(0.0088)	(0.0101)	(0.0081)	(0.0065)	(0.0060)	(0.0061)	(0.0065)				
arrears 3-12 months									0.006	0.0094	0.0062	0.0088*
									(0.0056)	(0.0057)	(0.0065)	(0.0052)
unsecured loans	0.0089	0.0131	0.0124	0.0082	0.0246***	0.0294***	0.0310***	0.0207***	0.0158*	0.0157*	0.0176*	0.0123
	(0.0125)	(0.0141)	(0.0153)	(0.0117)	(0.0073)	(0.0082)	(0.0089)	(0.0070)	(0.0092)	(0.0086)	(0.0098)	(0.0083)
roa	-0.0777	-0.0561	-0.0748	-0.0697	-0.0754*	-0.0358	-0.0398	-0.0714	-0.0999**	-0.0825*	-0.0845**	-0.1022**
	(0.0824)	(0.0774)	(0.0848)	(0.0737)	(0.0388)	(0.0397)	(0.0387)	(0.0443)	(0.0416)	(0.0442)	(0.0427)	(0.0455)
liquidity ratio	-0.0137	-0.0183	-0.0183	-0.0131	0.0035	0.0049*	0.0042	0.0037	-0.0118**	-0.0134**	-0.0123**	-0.0118**
	(0.0101)	(0.0128)	(0.0117)	(0.0109)	(0.0031)	(0.0027)	(0.0027)	(0.0031)	(0.0051)	(0.0053)	(0.0053)	(0.0054)
loan to deposit ratio	0.0098	0.0112	0.0101	0.0087	0.0108*	0.0079	0.0068	0.0106*	0.01	0.0055	0.0067	0.0088
	(0.0099)	(0.0096)	(0.0108)	(0.0086)	(0.0065)	(0.0055)	(0.0064)	(0.0058)	(0.0085)	(0.0074)	(0.0081)	(0.0079)
constant	0.6422	4.2328	4.9420	0.0068	-2.8085*	3.3455	3.9034*	-3.3021*	1.3195	2.4858	2.4012	0.9711
	(3.6595)	(3.6371)	(4.1165)	(3.9865)	(1.6703)	(2.1034)	(2.1605)	(1.8580)	(1.6720)	(1.9772)	(2.0559)	(1.7797)
Regional Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Year Effects	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No
Number of Obs	5505	4150	3734	5529	5169	4314	4192	4804	4556	4556	4556	4142
Wald chi2	230.8760	139.2814	206.6122	78.4029	189.6191	163.9232	197.9023	121.2484	192.729	159.4176	255.7187	110.8869
Prob>chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.3744	0.4394	0.4688	0.3582	0.2076	0.2341	0.2764	0.1652	0.1886	0.1949	0.2276	0.1483
Log Likelihood	-89.7446	-76.9242	-71.6503	-88.5724	-193.309	-181.006	-170.144	-197.135	-212.362	-210.728	-202.155	-215.265
AIC	215.4891	185.8484	195.3007	193.1448	424.6192	396.0134	396.2882	410.27	464.7246	457.4563	464.3106	446.5313
BIC	334.5306	287.1422	357.1568	246.0869	549.0775	504.297	573.8343	462.0877	593.2086	573.0919	657.0366	497.1627
AUROC Curve	0.9275	0.9510	0.9623	0.9001	0.8839	0.8692	0.9021	0.8154	0.8687	0.8804	0.8977	0.8253

This table reports results of the logistic regression model $\log[p_{i,t}/(1-p_{i,t})] = \beta_0 + \sum_{j=1}^{N} \beta_j X_{j,i,t-k} + \varepsilon_{i,t}$, 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 pay-out in year *t* given the vector of *j* explanatory variables at time *t-k*. Definitions of all explanatory variables are listed in Appendix 1. Standard errors are reported in parenthesis below their coefficient estimates and adjusted for both heteroskedasticity and within correlation clustered at the credit union level. The area under the receiver operator characteristic (ROC) curve is a measure of how well each specification can distinguish between failures survivors, with larger areas representing better performance. * (**) {***} indicates significance at the 0.10 (0.05) {0.01} level.

Table 7

1-, 2- and 3-year models supplemented with macroeconomic variables and subordinated debt

	1-Year Model				2-Year Model				3-Year Model			
Explanatory variables	**(1) National Unemp**	**(2) Regional Unemp**	**(3) CPI**	**(4) Sub Debt**	**(5) National Unemp**	**(6) Regional Unemp**	**(7) CPI**	**(8) Sub Debt**	**(9) National Unemp**	**(10) Regional Unemp**	**(11) CPI**	**(12) Sub Debt**
Size	-0.7486 **	-0.6162 **	-0.5362 *	-0.4727	-0.5340 ***	-0.3764 **	-0.4925 ***	-0.2969 *	-0.6710 ***	-0.5828 ***	-0.6401 ***	-0.5262 ***
	(0.3373)	(0.2944)	(0.3229)	(0.3041)	(0.1567)	(0.1522)	(0.1727)	(0.1536)	(0.1452)	(0.1369)	(0.1511)	(0.1446)
capital ratio	-0.1460 **	-0.0741	-0.1412 *	-0.1521 *	-0.1073 ***	-0.1197 ***	-0.1009 ***	-0.0944 **	-0.051	-0.0935 ***	-0.0474	-0.0409
	(0.0728)	(0.0655)	(0.0787)	(0.0841)	(0.0352)	(0.0389)	(0.0354)	(0.0396)	(0.0313)	(0.0319)	(0.0316)	(0.0274)
arrears > 12 months	0.0248 ***	0.0314 ***	0.0255 ***	0.0272 ***	0.0099	0.0101	0.0104 *	0.0144 **				
	(0.0081)	(0.0090)	(0.0080)	(0.0077)	(0.0064)	(0.0072)	(0.0062)	(0.0066)				
arrears 3-12 months									0.0089	0.0134 **	0.0078	0.0061
									(0.0055)	(0.0061)	(0.0055)	(0.0059)
unsecured loans	0.0117	0.0028	0.0120	0.0098	0.0245 ***	0.0167 **	0.0261 ***	0.0215 ***	0.0143	0.0093	0.0149 *	0.0092
	(0.0126)	(0.0133)	(0.0120)	(0.0117)	(0.0077)	(0.0084)	(0.0076)	(0.0072)	(0.0087)	(0.0103)	(0.0086)	(0.0082)
roa	-0.0608	-0.1242 *	-0.0665	-0.0550	-0.0483	-0.0489	-0.055	-0.0687	-0.0857 *	-0.0483	-0.0917 **	0.0126
	(0.0694)	(0.0735)	(0.0676)	(0.0691)	(0.0411)	(0.0427)	(0.0387)	(0.0426)	(0.0442)	(0.0514)	(0.0436)	(0.0085)
liquidity ratio	-0.0132	-0.0227 **	-0.0129	-0.0128	0.0040	0.0054 *	0.0041	0.0035	-0.0137 **	-0.0073	-0.0132 **	-0.0949 **
	(0.0115)	(0.0115)	(0.0105)	(0.0103)	(0.0030)	(0.0028)	(0.0031)	(0.0033)	(0.0057)	(0.0050)	(0.0053)	(0.0385)
loan to deposit ratio	0.0106	0.0094	0.0068	0.0081	0.0122 **	0.0133 **	0.0071	0.0106 *	0.0082	0.0107	0.0059	-0.0129 **
	(0.0075)	(0.0102)	(0.0084)	(0.0083)	(0.0054)	(0.0056)	(0.0054)	(0.0058)	(0.0079)	(0.0086)	(0.0076)	(0.0051)
national unemploy	0.5530 ***				0.5333 ***				0.3978 ***			0.0078
	(0.1803)				(0.1309)				(0.1245)			-0.0078
regional unemploy		0.2427 *				0.4221 ***				0.2709 **		
		(0.1425)				(0.1179)				(0.1143)		
CPI			0.2020				0.7113 ***				0.4858 ***	
			(0.2798)				(0.1519)				(0.1598)	
long-term sub debt				-0.1030				-0.0525				0.0660
				(0.0725)				(0.0701)				(0.0402)
short-term sub debt				0.1285				0.0411				0.0055
				(0.0895)				(0.0656)				(0.0510)
constant	-0.7034	0.2227	-0.0036	-0.3107	-3.5394 ***	-4.7735 ***	-2.2254	-2.9092 *	1.04	0.4001	2.0265	1.6161
	(3.6235)	(3.3330)	(3.6767)	(3.5833)	(1.7054)	(1.7469)	(1.8100)	(1.6686)	(1.6917)	(1.5671)	(1.6798)	(1.6690)
Number of Obs	6117	5588	6117	6117	5309	4867	5309	5309	4556	4181	4556	4546
Wald chi2	83.5854	49.1217	87.4427	86.4558	152.8874	117.1173	155.3004	141.7283	137.6119	144.6949	138.9997	119.1272
Prob>chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.3766	0.2820	0.3523	0.3575	0.2084	0.1838	0.2107	0.1789	0.1756	0.155	0.1728	0.164
Log Likelihood	-90.8787	-65.9176	-94.4214	-93.6562	-195.837	-153.162	-193.451	-201.251	-215.769	-174.926	-216.499	-218.727
AIC	199.7574	149.8352	206.8429	207.3125	406.0218	324.3248	404.9032	422.5024	449.5392	367.853	450.9987	459.4547
BIC	260.2268	209.4906	267.3123	274.5007	465.2163	382.7369	464.0977	488.274	507.357	424.8978	508.8165	530.0967
AUROC Curve	0.9178	0.8562	0.9016	0.9066	0.8693	0.8713	0.8624	0.8381	0.8682	0.8810	0.8572	0.8384

This table reports results of the logistic regression model $\log[p_{i,t}/(1-p_{i,t})] = \beta_0 + \sum_{j=1}^{N} \beta_j X_{j,i,t-k} + \varepsilon_{i,t}$, 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 pay-out in year *t* given the vector of *j* explanatory variables at time *t-k*. Definitions of all explanatory variables are listed in Appendix 1. Standard errors are reported in parenthesis below their coefficient estimates and adjusted for both heteroskedasticity and within correlation clustered at the credit union level. The area under the receiver operator characteristic (ROC) curve is a measure of how well each specification can distinguish between failures survivors, with larger areas representing better performance. * (**) {***} indicates significance at the 0.10 (0.05) {0.01} level.

Appendix 1: Source and definition of explanatory variables

Variables	Definition	Source[a]	Formula
Capital Adequacy:			
simple capital ratio	Total Capital/Total Assets	Form CY	100*(CY_2S/CY_2P)
risk-adjusted capital ratio	Total Risk-adjusted Capital/Total Assets[b]	Form CY	100*[(CY_32A + Min{CY_32B, CY32C})/CY_32D]
Asset Quality:			
total arrears	Net Liabilities in Arrears/Total Net Liabilities[c]	Form CY	100*(CY_15C/CY_14H)
arrears 3-12 months	Net Liabilities 3-12 months in Arrears/Total Net Liabilities	Form CY	100*(CY_15A/CY_14H)
arrears > 12 months	Net Liabilities > 12 months in Arrears/Total Net Liabilities	Form CY	100*(CY_15B/CY_14H)
provisions to loans	(General + Specific Provisions)/Total Loans to Members	Form CY	100*[(CY_16E + CY_16K)/CY_14F]
provision coverage	(General + Specific Provisions)/Net Liabilities I Arrears	Form CY	100*[(CY_16E + CY_16K)/CY_14H]
unsecured loans	Unsecured loans/Total Assets	Form CY	100*(CY_1F/CY_2P)
Management:			
size	Natural log of Total Assets	Form CY	LN(CY_2P)
cost-to-income	Total Expenditure/Total Income	Form CY	100*(CY_4Q/CY_3P)
management expense	Management Expenses/Total Assets	Form CY	100*(CY_4D/CY_2P)
admin expense	Administrative Expenses/Total Assets	Form CY	100*(CY_4A/CY_2P)
members	Number of qualifying members	Form CY	CY_A1
full-time staff	Number of full-time employees	Form CY	CY_A5
Earnings:			
return on assets	After-tax Profit (Loss)/Total Assets	Form CY	100*(CY_7/CY_2P)
Liquidity:			
liquidity ratio	Total Liquid Assets[d]/Total Relevant Liabilities[e]	Form CY	100*(CY_29E/CY_30D)
loans to deposits	Total Loans/Total Members' Share Balance	Form CY	100*(CY_14F/CY_2T)
Miscellaneous:			
total sub debt	Total Subordinated Debt/Total Assets	Form CY	100*(CY_25E/CY_2P)
short-term sub debt	Short-term Subordinated Debt/Total Assets	Form CY	100*(CY_2Q/CY_2P)
long-term sub debt	Long-term Subordinated Debt/Total Assets	Form CY	100*(CY_2R/CY_2P)
regional dummies[f]	A set of 12 dummies (1 for each region) equal to 1 if the credit union I in that region, and 0 otherwise	Form CY	Derived from address
regional unemployment	Regional Unemployment Rate	OECD regional statistics	
national unemployment	National Unemployment Rate		
cpi	Consumer Price Index		

Notes: (a) Form CY is the annual regulatory return submitted by credit union to the PRA (and previously the FSA as legacy supervisor); (b) total risk-adjusted capital is calculated for larger version 1 and version 2 credit unions and equals total capital plus the lesser of net provisions (i.e., total provisions less minimum specific provisions) or 1% of total assets;(c) net liabilities equal total loans plus accrued interest less the members' share balances used to secure the loan; (d) total liquid assets equals the sum of qualifying cash and bank balances, investments realizable within 8 days, unused committed facilities and unused overdrafts; (e) total relevant liabilities equal the sum of unattached shares and liabilities with an original or remaining maturity of less than three months; (f) we group credit unions into 12 regions: North East England, North West England, Yorkshire and the Humber, East Midlands, West Midlands, East England, Greater London, South East England, South West England, Wales, Scotland and Northern Ireland.

Appendix 2: Correlation matrix

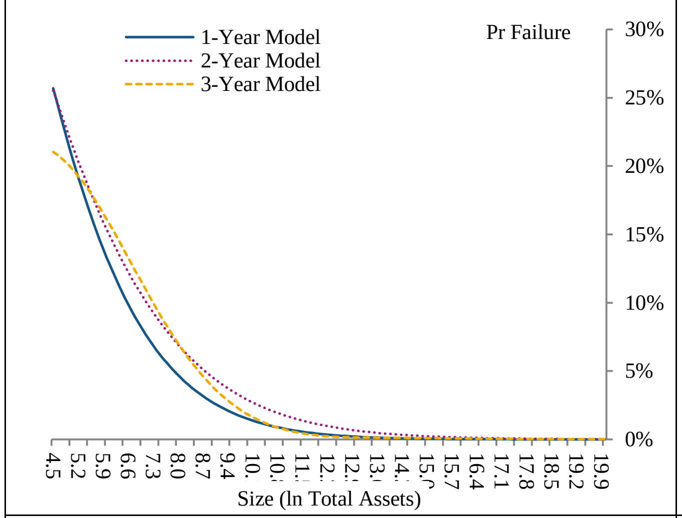
	Variable	1	2	3	4	5	6	7	8	9	10
1	size	1.0000									
2	capital ratio	0.1370*	1.0000								
3	risk-adjusted capital ratio	0.0281	0.7854*	1.0000							
4	total arrears	-0.2328*	-0.0332*	0.3082*	1.0000						
5	arrears 3-12 months	-0.1014*	-0.0182	0.1959*	0.4409*	1.0000					
6	arrears>12 months	-0.0899*	-0.0554*	0.2867*	0.6219*	0.3376*	1.0000				
7	provisions to loans	-0.1976*	-0.0727*	0.2805*	0.8643*	0.2778*	0.6489*	1.0000			
8	provision coverage	0.0950*	0.0094	-0.0720*	-0.2755*	-0.2174*	-0.1557*	-0.1211*	1.0000		
9	unsecured loans	0.2839*	-0.0079	-0.0310	-0.0001	0.0493*	0.0283*	-0.0312*	0.0059	1.0000	
10	management expense	-0.0255*	0.0295*	-0.0903*	-0.0107	0.0458*	-0.0108	-0.0108	-0.0167	0.0695*	1.0000
11	admin expense	-0.1701*	-0.0429*	0.1529*	0.0713*	0.0490*	-0.0633*	0.0562*	-0.0398*	-0.0396*	0.0345*
12	cost-to-income	-0.2404*	-0.2433*	-0.0521	0.3277*	0.1865*	0.1692*	0.3435*	-0.1117*	0.0727*	0.0645*
13	roa	0.1094*	0.3061*	0.0760*	-0.2823*	-0.1536*	-0.1614*	-0.2950*	0.0787*	-0.0512*	-0.0008
14	loans-to-deposits	0.1833*	0.0770*	0.1352*	0.0376*	0.1332*	0.0478*	0.0304*	-0.0045	0.7192*	0.0715*
15	liquidity ratio	-0.2743*	0.2685*	0.2639*	0.1133*	-0.0091	0.0616*	0.0793*	-0.0274*	-0.3440*	0.0162
16	Members	0.0194	0.0694*	0.0816*	0.0740*	0.0251*	0.0201	0.0648*	-0.0278*	0.0453*	-0.0096
17	full-time staff	0.1513*	0.0240*	0.0851*	-0.0369*	-0.0251*	-0.0216*	-0.0307*	0.0229*	0.0246*	-0.0040
18	total sub debt	0.2901*	0.0507*	0.1109*	-0.0495*	-0.0363*	-0.0387*	-0.0343*	0.0161	0.0914*	0.0059
19	long-term sub debt	0.0194	0.0694*	0.0816*	0.0740*	0.0251*	0.0201	0.0648*	-0.0278*	0.0453*	-0.0096
20	short-term sub debt	0.0265*	0.0949*	0.0945*	0.0590*	0.0354*	0.0330*	0.0691*	-0.0289*	0.0540*	0.0163

	Variable	11	12	13	14	15	16	17	18	19	20
11	admin expense	1.0000									
12	cost-to-income	0.2670*	1.0000								
13	roa	-0.0981*	-0.8163*	1.0000							
14	loans-to-deposits	0.0506*	0.1028*	-0.0265*	1.0000						
15	liquidity ratio	0.0853*	0.0185	0.0194	-0.2824*	1.0000					
16	members	0.0882*	0.1117*	-0.1122*	0.0396*	0.0615*	1.0000				
17	full-time staff	-0.0148	-0.0284*	0.0136	0.0266*	-0.0330*	0.0050	1.0000			
18	total sub debt	0.0538*	0.0181	-0.0162	0.0854*	-0.0734*	0.0217*	0.0911*	1.0000		
19	long-term sub debt	0.0882*	0.1117*	-0.1122*	0.0396*	0.0615*	1.0000*	0.0050	0.0217*	1.0000	
20	short-term sub debt	0.0801*	0.0957*	-0.0802*	0.0431*	0.0431*	0.6756*	0.0084	0.0293*	0.6756*	1.0000

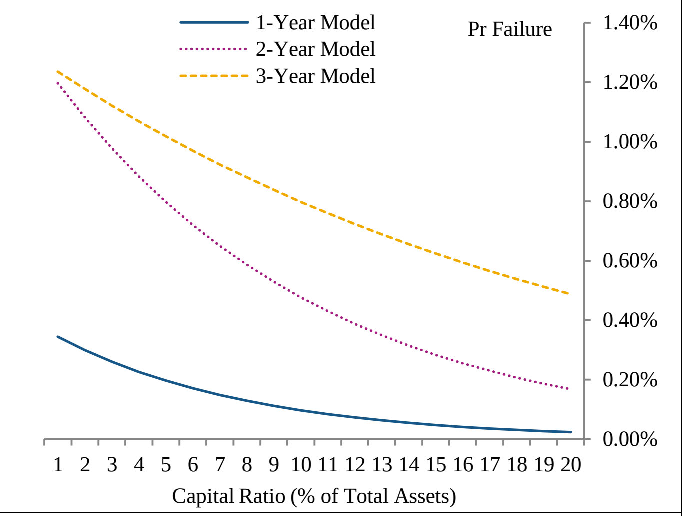
Source: Bank of England regulatory data and authors' calculations. * indicates significant at the 0.10 level.

Appendix 3: Marginal effects of explanatory variables

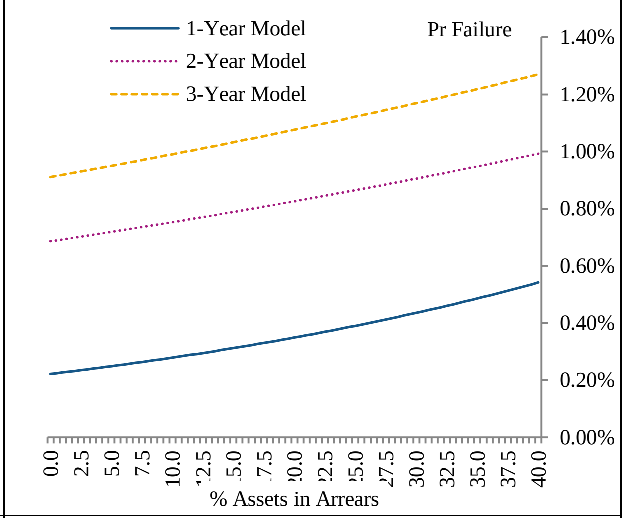
Panel A: Size (ln Total Assets)



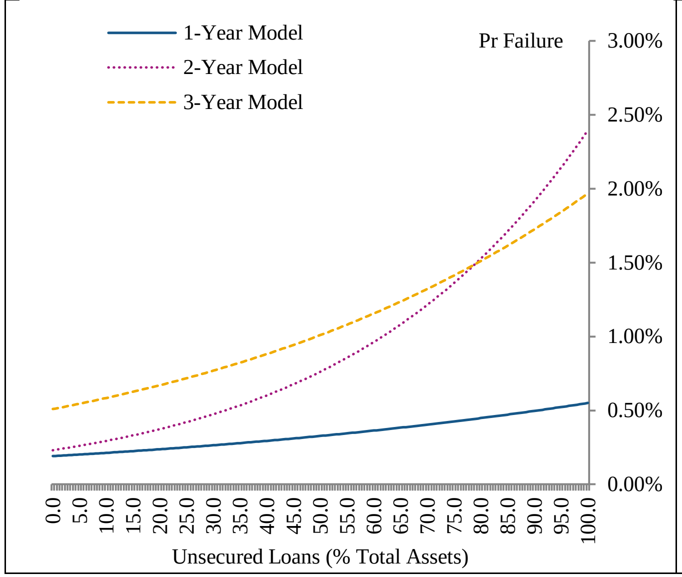
Panel B: Capital (% of Total Assets)



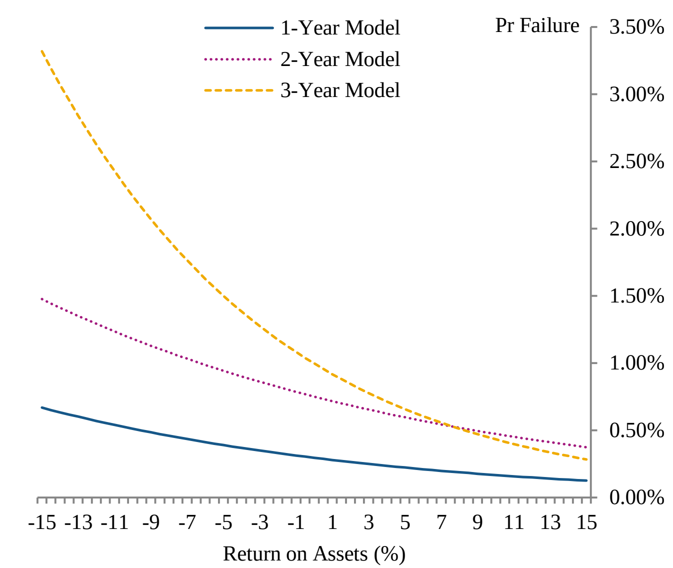
Panel C: Arrears (% of Total Assets)



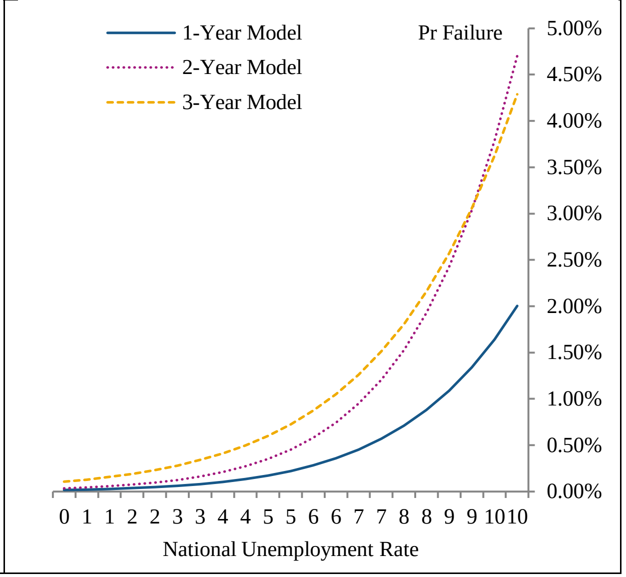
Panel D: Unsecured Loans (% of Total Assets)



Panel E: Return on Assets



Panel F: National Unemployment Rate



Source: Authors’ calculations.