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UK deposit-taker responses to the financial crisis: what are the lessons?

William B Francis

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Abstract

While the financial crisis took a large toll on the UK banking industry overall, some institutions were forced to undertake more intensive efforts to deal with the economic downturn and onset of financial difficulties. This study examines whether and how the characteristics of these institutions leading up to and during the crisis differed from those of institutions that dealt with the turmoil using less intensive efforts. I find that, under the regulatory environment existing before the crisis, institutions that ultimately resorted to more intensive efforts (ie debt-equity swaps, mergers with/acquisitions by stronger competitors and outright closure) to deal with financial difficulties had significantly weaker financial profiles as measured by a set of attributes reflecting capital adequacy, asset quality, management skills, earnings performance and liquidity. This study's framework is useful for characterising financial vulnerability in a regulatory regime similar to that in place before the crisis and, in that respect, is helpful for highlighting weaknesses of the previous regime and for understanding the recent regulatory emphasis on, among other things, a non risk-based capital requirement.

Key words: Regulation, leverage ratio, bank failure, vulnerability, logit.

JEL classification: G21, G28, G38.

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Summary

While the financial crisis had an adverse effect on the UK banking sector overall, some institutions fared worse than others in dealing with the onset of economic stresses. Those that fared worse were forced to undertake a host of more intensive actions, including debt-equity swaps (a form of bail-in), mergers with/acquisitions by stronger competitors and outright closure. But what was it about these firms that made them less capable of dealing with the downturn and what can regulators learn from these cases?

Toward addressing these questions, this paper takes a closer look at what drove UK deposit-takers' responses to the crisis. It specifically investigates the role that firm-level financial profiles played in influencing the intensity of such responses. It uses data spanning 2005 to 2011 on UK building societies, which, because of their mutual status, face similar constraints in their ability to tap external capital markets. This approach can help isolate the effect of financial condition, as opposed to market access, on response intensity.[1]

The study groups firms into two separate and distinct categories according to the intensity with which they responded to the crisis. The first includes firms that resorted to more intensive efforts (i.e., debt-equity swap, mergers, acquisition, closure), while the second is effectively a catch-all category, consisting of firms that responded in other, less intensive, ways. It uses well-known empirical techniques (i.e., limited dependent variables models) and financial attributes from the research examining the determinants of bank failure/distress to investigate whether these factors are also useful in explaining UK deposit-taker response intensity. The financial factors examined include the well-known CAMEL attributes that analysts typically use to evaluate the condition of deposit-takers and that previous research finds useful in profiling banking institutions: Capital adequacy, Asset quality, Management capability, Earnings performance and Liquidity.

The paper's key result is that a small set of these financial attributes effectively distinguishes firms that undertook less intensive responses (i.e., less vulnerable firms) from those that resorted to more intensive responses (i.e., more vulnerable firms) to deal with the onset of economic stress. I also find that, compared with risk-based capital measures, a simple leverage (i.e., capital to assets) ratio was better at classifying response intensity and, therefore, characterizing financial vulnerability under the prudential regulatory regime that existed before the crisis. This evidence supports the recent regulatory emphasis on updating the regime to include consideration of non risk-based capital measures alongside risk-based measures.

A useful aspect of the modelling approach discussed in this paper is its objective consideration of a broad set of financial attributes and their interactions in profiling firm-level vulnerability. This approach means, for example, that low capital ratios would not be the sole criterion for triggering heightened supervisory attention. Rather, concerns about an institution's ability to deal with stress would be based on the financial CAMEL attributes as a group and their relative importance in explaining how firms responded to previous economic downturns. The output from the approach could also complement regular stress-testing efforts and assist in evaluating firms' recovery plans by pointing to

[1] Extending this analysis to include data from the wider UK banking sector is an area for future work.

firms that exhibit features similar to those that were less capable of dealing with the onset of adverse economic conditions in the past.

While the profiling approach discussed in this paper may be of interest to regulators for use in off-site monitoring, a key caveat limits its use in that capacity. In particular, the estimates in this study are conditioned on a prudential regime that excluded a leverage requirement. This study's findings, as a result, reflect UK deposit-taker behaviour that could conceivably differ from that under a regime that includes such a requirement (e.g., Basel III). This means that the set of financial measures – and the relative importance of each measure – found useful in distinguishing relatively more vulnerable firms in this study may be different under a revised prudential framework if deposit-takers alter business models and capital management practices in response. Still, the results are useful for highlighting potential shortcomings of the pre-crisis regulatory regime and for gaining initial insight into the effects of proposals aimed at addressing such flaws.

1 Introduction

The financial crisis had a significant impact on the banking sector in the United Kingdom. Several institutions required government assistance to remain going concerns and continue vital intermediary activities. A number of these cases were well-publicized and involved large, systemically important institutions with relatively complex business models comprising a mix of retail, commercial and investment banking activities.[2] In addition to direct government intervention, financial institutions were forced to undertake costly responses to deal with the onslaught of the financial crisis. These responses varied considerably across firms, with some making more subtle, less intensive alterations to their capital and balance sheet management practices, while others taking less subtle, more intensive actions involving debt-equity swaps, mergers with/acquisitions by stronger peers and outright closure. A key distinction with respect to these more intensive responses is that firms that resorted to such measures no longer existed in the same shape or form as they did prior to the crisis.

The purpose of this paper is to explore the determinants of firms' choice of response intensity during the crisis. If this choice were driven by the underlying financial condition of the respondent heading into or during the crisis, then documenting the driving factors may provide insight into the sources of financial vulnerability that existed in the previous regulatory environment. Such insight could help highlight shortcomings of the previous regime and illustrate possible effects of proposals aimed at addressing such regulatory failures.

To evaluate differences, the study groups firms into two separate and distinct categories according to the intensity with which they responded to the crisis. The first includes firms that resorted to more intensive (and potentially more costly and difficult to implement) efforts to deal with the onset of the crisis. These 'more intensive' efforts include debt-equity swaps (a form of 'bail-in'), mergers with and acquisitions by stronger competitors and outright failure/closure. The second group is effectively a catch-all category, consisting of firms that did not rely on these more intensive measures, but instead responded in other, 'less intensive', ways to mounting pressures during the crisis.[3]

The study focuses on evaluating whether and how the firm-level financial characteristics heading into and during the crisis differed between these two categories. It focuses on the period 2005 to 2011, which spans the course of the crisis, and captures both an upturn and downturn in economic conditions. Finding that characteristics differ would provide some initial clues about the sources of financial vulnerability more broadly. These findings can also shed light on the extent to which market or regulatory failures promoted these sources. This evidence is necessary for understanding the need for regulatory intervention and, where relevant, shaping appropriate policy responses.

This study is related to the research examining the determinants of bank failure and bank distress and contributes to the literature on risk profiling. It extends well-known empirical techniques (i.e., limited dependent variables models) and factors from this

[2] See Rose and Wieladek (2012) for more detail on public interventions during the crisis.
[3] We recognize that these 'less-intensive' responses may also have implications for the overall macro economy, especially if they lead to a reduction in credit supply or increase in underwriting standards. Refining the definitions of response intensity into more granular measures and evaluating the underlying drivers and effects on the overall macro economy is an area for future research.

research to investigate whether these factors are also useful in explaining the responses taken during the recent crisis. The financial factors examined include attributes that analysts typically use to evaluate the condition of banks and that previous research shows are useful in characterizing problem banks: capital adequacy, asset quality, management capability, earnings performance and liquidity.

The extent to which firms could access external capital markets may have also affected response intensity during the crisis. To control for cross-sectional differences in this ability, the study uses data from the UK building society sector. Because of their mutual form of ownership, firms in this sector are similarly restricted in their ability to access external capital. As a result, employing data from this sector facilitates a cleaner examination of the association between financial condition and firm-level responses as compared with a setup that includes all UK banking institutions.[4]

By way of preview, I find that a small set of financial attributes reflecting capital adequacy, asset quality, management capability, earnings performance and liquidity is significant in explaining response intensity during the crisis. This set effectively distinguishes firms that undertook less intensive responses from those that resorted to more intensive responses to deal with the onset of economic stress. I also find that, compared with risk-based capital measures, a simple leverage (i.e., capital to assets) ratio is better at classifying response intensity under the previous regulatory environment. This result highlights a weakness of the previous regulatory regime and provides support for the recent regulatory proposals related to a non-risk-based capital requirement.

The remainder of this paper proceeds as follows. Section 2 briefly discusses the empirical risk profiling techniques and the research on bank failure and distress relevant to this study. Section 3 describes the data used to categorize firms by response intensity and the construction of explanatory measures. Section 4 discusses and methodology and how it can be used to identify aspects of firm-level vulnerability. Section 5 reviews estimation results, while Section 6 sets out policy implications. Section 7 concludes.

2 Empirical risk profiling

This section provides a brief overview of econometric profiling techniques relevant to this study. It also describes the role of these techniques in identifying problematic financial institutions and their use by supervisors in off-site surveillance programmes.

2.1 Relevant econometric profiling techniques

In the context of banking, econometric profiling techniques aim to explain variations in the likelihood of a key event or outcome, e.g., failure, rating downgrade, distress, with reference to a range of structural and financial variables. Discrete or limited dependent variables techniques feature prominently in much of this work. These include, for example, binary or ordinal level logit (or probit) models to explain variations in the

[4] A separate evaluation of the drivers of UK banking entities' responses during the financial crisis is an area for future research.

likelihood of two or more possible ordinal outcomes such as failure or non-failure, with an underlying logistic (normal) probability distribution.[5]

While standard logit models contain only fixed parameters, mixed logit models contain both fixed and random parameters.[6] In standard logit models the probability of a particular outcome for an individual firm is simply a weighted function of its fixed parameters (i.e., assuming homogeneity) with all other behavioural information captured by the error term. By contrast, in mixed logit models the probability of a particular outcome for an individual firm is determined by the mean influence of each explanatory variable with a fixed parameter estimate within the sample, plus, for any random parameter, a parameter weight drawn from the distribution of individual firm parameters estimated across the sample. Thus, mixed logit models can capture observed and unobserved heterogeneity within and across firms.

A common strength of these econometric profiling techniques relative to other approaches is their objectivity. Variables will be included in the model only if they are statistically significant and they will be weighted according to their importance in determining variations in the probability of the outcome in question (e.g., firm-level failure or distress). As a result, they are not subject to biases that can arise in other approaches that rely on simple rules-of-thumb for assigning weights.

2.2 An example of risk profiling in practice

In 1993 the US Federal Reserve introduced the Financial Institutions Monitoring System (FIMS), a new off-site monitoring system for identifying financially troubled institutions in between on-site supervisory visits.[7] FIMS consists of two separate and distinct models. The first, known as the FIMS rating model, provides an estimate of what a bank's so-called CAMEL rating would be if it were assigned during the current quarter.[8] The acronym CAMEL stands for the five dimensions of performance considered during on-site evaluations of banks, i.e. capital adequacy, asset quality, management, earnings and liquidity, to determine an overall performance rating on a scale from 1 (sound) to 5 (unsound) for a bank.[9] The second, known as the FIMS risk rank model, provides an estimate of a bank's risk of failing at some point during the subsequent two years.

[5] While not used in this study, multi-nominal and nested logit models allow for a range of outcomes, facilitating analysis of varying degrees of an event or outcome of interest, e.g., varying degrees of distress or nearness to regulatory capital requirements.

[6] These mixed logit models are also known as panel data logit or probit models (see, for example, Verbeek (2005) for more details on these models).

[7] Cole et al. (1995) describe the econometric set up of this system and assess its performance relative to an econometrically less advanced predecessor system that relies on simple rules-of-thumb and judgmentally-based variable weightings.

[8] US bank regulators assign ratings to banks roughly once every 18 to 24 months based on more extensive on-site examinations. Cole and Gunther (1995), however, provide evidence that the shelf life of these ratings is approximately 6 months, suggesting that there is considerable scope for these ratings to change rapidly in between on-site examinations and especially during turbulent economic conditions.

[9] Introduced in the US in 1979, the Uniform Financial Rating System, also known as the CAMEL ratings system, outlined a common set of criteria across the three primary banking regulators for use by examiners in assessing the health of banking institutions. Bank condition was originally assessed on the basis of five key components of capital adequacy, asset quality, management competency, earnings performance and liquidity. In 1996, a separate component covering sensitivity to market risk was added, leading to the CAMELS acronym.

The FIMS rating model and the FIMS risk rank model employ an ordinal level logistic regression methodology and a binary probit methodology, respectively. Essentially, these models relate the probability of certain outcomes to a number of explanatory variables. These explanatory variables include thirty structural and financial ratios selected from the financial literature and financial ratios commonly used in supervisors' examination reports. They also include a number of regional economic variables to account for the potential effects of local economic conditions on bank health. The FIMS rating model also includes prior period CAMEL and CAMEL component variables.

The models are fitted with available data, including regulatory Call Report data submitted by firms. A step-wise procedure of excluding insignificant variables is used to optimise the explanatory power of the model. Once fitted, the models can be used to characterize CAMEL scores and a risk rating (i.e., failure probability) for a specific firm based on the most recent data available for this firm.

FIMS compares well with predecessor models, which focused on subjectively selected financial and structural variables to assess banks' financial condition. A key shortcoming of the predecessor models is that they subjectively weighted these variables without regard to actual statistical correlations between these variables and banks' financial condition. Running FIMS over the same data as the predecessor models shows very significant improvements in the accuracy of predictions about firms' financial condition.

2.3 Modelling bank failure and distress

This study is related to the vast literature examining failure and distress at the bank level.[10] This subsection discusses common themes from this research and their relevance for assessing the characteristics of response intensity in this study. Of note, a key objective of this previous research was to inform and shape off-site surveillance systems for use in banking supervision.

Our brief survey of the literature indicates that this line of research relies almost exclusively on statistical analysis of financial ratios constructed from public accounting or regulatory return data to identify a set of financial characteristics useful in explaining and assessing the likelihood of bank failure or the timing of bank failure (see, for example, Cole et al. (1995), Cole and Gunther (1995), Whalen (1991), Wheelock and Wilson (1995, 2000), Cole and Wu (2009)). Limited dependent variable methods (e.g., logistic and probit models as described above) feature prominently in many studies due to the discrete nature of the events of primary interest to supervisors: failure, closure or downgrade. In addition, many of the chosen financial measures reflect aspects of capital adequacy, asset quality, management skills, earnings performance and liquidity, the so-called CAMEL attributes employed by the US banking authorities to rate banks.

As highlighted above, Cole et al. (1995) is a typical example of this line of work.[11] Using a binary probit model, the authors estimate the relationship between regulatory Call

[10] See, for example, Demirguc-Kunt (1989), Demyanyk and Hasan (2009), and Sahajwala and Van den Bergh (2000) for more comprehensive surveys of this work.
[11] Indeed, the article describes the details underlying much of the framework underlying the US Federal Reserve System's primary early warning system currently used as part of their formal off-site surveillance programme for monitoring over 6,000 commercial banks in the US each quarter (see Section 1020.1 of the

report data and US bank failures spanning 1985 to 1993 and find that nine ratios are significant in explaining failures during that time. Four relate to asset quality and include the ratios of loans past due 30-89 days and still accruing interest, of loans past due 90 or more days and still accruing interest, of nonaccrual loans, and of foreclosed real estate, all expressed as a percentage of total assets. Higher ratios of each are associated with a greater likelihood of failure. The remaining five variables, also expressed as a proportion of assets, include tangible equity capital, net income, loan loss reserves, investment securities, and large (over $100,000) certificates of deposit. The first three are proxies for capital adequacy, earnings performance and management quality, respectively, while the last two together reflect liquidity measures. The underlying aim of their study was to identify a set of characteristics and factor weights useful for identifying early banks exhibiting emerging issues that warrant closer supervisory attention.

While US experience underpins many of these studies, presumably because of the large sample of failures that occurred in that country during the last major banking crisis in the late 1980s and early 1990s, studies of banking problems in other countries tend to take a similar approach. For example, using a series of single-period logit models (and multi-period hazard models for Latin America), Arena (2008) examines the determinants of bank failure in East Asia (and Latin America). He shows that bank-level fundamentals, as captured by CAMEL-related factors, explain bank failure. Dabos and Escudero (2004) employ proportional hazard modelling to evaluate the determinants of time to failure for banks in Argentina. They find that several bank-specific factors related to the CAMEL framework are useful in explaining survival time. Kiefer and Gomez-Gonzalez (2007) evaluate the determinants of bank failures during the financial crisis in Colombia also using a proportional hazard approach. They find that key ratios related to capital adequacy, earnings performance, management efficiency, loan composition and bank size are useful in explaining time to failure. In their specification, the capitalization ratio is the most significant indicator explaining bank failure, with increases in this ratio reducing the hazard rate of failure.

Studies based on data from countries a bit closer to the UK include Poghosyan and Cihak (2009) and Gunsel (2010). The former uses a unique dataset of individual bank distress across the European Union from the mid-1990s to 2008 to analyze the causes of banking distress in Europe. The authors find that CAMEL measures related to capitalization, asset quality and profitability and liquidity help explain the likelihood of distress and that thresholds based on these measures are useful for distinguishing healthy institutions from those vulnerable to financial distress.

Gunsel (2010) also uses several CAMEL covariates to investigate the determinants of the timing of bank failure in North Cyprus over the period 1984 to 2002. Discrete-time logistic survival analysis reveals that weak asset quality (total loans as a percentage of total assets), low liquidity (liquid assets as a percentage of total assets) and high credit to the private sector (ratio of the private credit to gross domestic product) explain the survival time of banks in North Cyprus.

Federal Reserve System Commercial Bank Examination Manual at http://www.federalreserve.gov/boarddocs/supmanual/cbem/cbem.pdf for more detail).

3 Data

I obtained firm-level financial information from regulatory returns filed with the Financial Services Authority. In particular, QFS returns provide the source of data from 2005 to 2008, while FSA001, 002, 003 and 015 returns supply data since 2008. These returns are submitted by all building societies and provide key balance sheet and income statement information. They also include a host of other metrics, including measures of arrears rates, useful for tracking the condition of societies over time and relative to peer institutions. I gathered quarterly returns from year-end 2005 to year-end 2011 for all UK societies, which, ranged between 47 to 58 societies per quarter.

3.1 Deposit-taker responses

As mentioned, this study groups firms into two separate categories depending on the intensity of the actions they took in response to the unfolding crisis. The first contains firms that relied on more intensive actions, including debt-equity swaps (a form of 'bail-in'), mergers with and acquisitions by stronger competitors and outright closure or failure, to deal with mounting pressures from the crisis. The second comprises all other firms and captures those that were able to deal with the crisis without resorting to material changes to balance sheet management practices, ownership structures or regulatory intervention. A key distinction between firms in the first (more intensive) category and those in the second (less intensive) category is that the former no longer existed in the same shape or form as they did prior to the crisis.

To group firms according to this process, I reviewed information from the KPMG Building Society Annual Database and statistics reported on the UK Building Society Association's website. Both of these sources discuss mergers and acquisitions in the sector over time. I supplemented this review by reading press releases and discussing the transactions with supervisors to understand better the reasons for these transactions.

To date the response, I used the earlier of either the quarter in which the transaction occurred or the quarter corresponding to the last regulatory return submitted by the more intensive respondent. Using this process, I identified twelve institutions, or roughly twenty-percent of the building society sector, that resorted to more intensive measures to deal with the crisis.[12] Tables 1 and 2 provide more detail on the timing and evolution of the sample of responses leading up to and during the crisis.

Figure 1 shows that the end result of these more intensive responses was to decrease the number of building societies from 59 at the end of 2007 and just before the height of the crisis to an historical low of 47 at the end of 2012. While the rates at which the number of building societies declined over the recent crisis is below that experienced in previous episodes of banking stress in the United Kingdom, it is above those reported since the last half of the 1990s, a period of significant demutualization in this sector. Providing some context, Figure 2 displays rolling five-year rates of decline since 1980. The figure shows that the rates recorded at the end of 2010 and 2011 are roughly similar to those reported at the tail end of the last major episode of banking problems in the United Kingdom during the late 1980s and early 1990s.

[12] These transactions included nine mergers, one acquisition, one debt-equity swap and one closure involving special administration procedures.

3.2 Description of variables

Consistent with the literature examining the determinants of problem banks, I constructed several variables to measure aspects of firm-level vulnerability. These measures reflect the CAMEL attributes discussed above that previous research finds useful in explaining bank failure and distress. Table 3 lists these variables, their definition and expected association with response intensity.

To reflect capital adequacy, I evaluated three ratios, which differ according to the mix of capital elements included in the numerator and the measure of assets used in the denominator. I include two risk-based capital ratios, namely the tier 1 risk-based capital ratio (T1RBC) and the total risk-based capital ratio (TOTRBC), which reflect the ratios of tier 1 capital and total regulatory capital to risk-weighted assets, respectively. I am particularly interested in understanding the effect of leverage on the choice of response. Finding a negative association (with the likelihood of response intensity) would be consistent with the idea that firms with higher capital ratios are less vulnerable and better placed to deal with an outbreak of adverse economic conditions. Consequently, I also include the tier 1 leverage ratio (T1LEV), measured as the ratio of tier 1 capital to total non-risk-weighted assets. I expect all of these ratios to be inversely associated with the likelihood of more intensive responses.

Prior to the introduction of Basel II in 2007, one might expect these three capital measures to be highly correlated. This conjecture stems from the fact that the risk-based capital measures under Basel I were much less sensitive to risk compared with Basel II. Basel II introduced much more granular risk-weights and allowed institutions to use their own-estimates (i.e., internal models) of default likelihood and loss given default to set capital requirements. Figure 3 shows how the correlation among these three variables evolved over time and clearly shows how the non-risk-based leverage ratio became less correlated with the risk-based measures after the implementation of Basel II.

To control for asset quality, I examined nine ratios. Five of these ratios reflect varying degrees to which a building society's asset portfolio is past due or nonperforming. The first four measure granular arrears rates on (i) residential real estate loans to individuals (ARFSRP_I), (ii) residential real estate loans to others (ARFSRP_O), (iii) partially or unsecured loans to individuals (AROTHR_I) and (iv) partially or unsecured loans to others (AROTHR_O). The last of the five measures total repossessed loans as a percentage of total loans (REPOSSES). I expect each of these five measures to be positively related to the likelihood of needing a more intensive response.

In addition to these performance measures of asset quality, I include two measures of a building society's own estimate of expected losses: the ratio of total loan loss provisions to total arrears (PROV_ARS) and the ratio of total loan loss provisions as a percentage of total loans (PROV_LNS). Finally, I also examine two broader measures of asset risk proxied by the ratios of total loans to total assets (LNS_ASST) and total risk-weighted assets to total assets (RWA_ASST). Again, I expect all of these measures to be positively associated with the probability of needing more intensive efforts.[13]

[13] We recognize that the use of firms' provision estimates may be an imprecise measure of expected losses, especially in light of the managerial biases to report more favourable asset quality assessments and the shortcomings of the incurred loss model underlying accounting standards governing loan loss recognition in the UK.

I included several proxies for management quality, most of which measure balance sheet composition. In particular, I employ three ratios of loan portfolio make-up: residential real estate concentration (RESRE_TA), other fully-secured loans (OTH_FSOL), and residential development loans (DEVEL_TA), each expressed as a percentage of total assets. Ex ante, the association between probability of response intensity and portfolio composition is not known. I also include a measure of size (SIZE), the natural log of total assets, expected to be negatively related to the likelihood of a more intensive response based on the conjecture that larger building societies may be better able to diversify their portfolio across regions or borrower types (see, for example, Calomiris and Mason (2000)). Finally, to proxy management inefficiency, I incorporated the ratio of total non-interest cost to income (EFF_NCY), which I expect to be positively associated with a more intensive response probability.[14]

Prior research has also found that measures of earnings performance are useful in explaining bank failure. To capture earnings performance, I include the ratio of after-tax income to total average assets (ROA) and the ratio of after-tax net income to total average equity (ROE). In computing the ratios, I annualize earnings and average (using a two-point, simple average) assets and equity using reported values from the beginning and ending points of the relevant earnings period. I expect these measures to be negatively associated with the likelihood of requiring more intensive actions.

To proxy liquidity risk, I incorporated two measures. The first is the liquid assets to total assets ratio (LIQ_ASST), where liquid assets reflects cash, short-term deposits with other financial institutions, short-term government securities and marketable equity securities. The sign on this variable is, ex ante, ambiguous.[15] The second is the ratio of total loans to deposits (LNS_DEP). A higher ratio suggests a potentially greater reliance on wholesale, non-deposit funding, which may increase the likelihood of requiring more intensive strategies to deal with distress, especially in more volatile economic conditions. Accordingly, I expect this measure to be positively associated with response intensity.

3.3 Characteristics of response intensity

This subsection reviews statistics for firms that responded more intensively and less intensively to the crisis. It also examines whether these key statistics differ at different points in time leading up to and during the height of the crisis. As mentioned earlier, there were twelve instances of more intensive responses to the crisis during the 2008 to 2011 timeframe. To take into consideration the deteriorating economic conditions and attendant effects on firm-level health, the analysis was undertaken at six different points in time spanning three stages of the crisis: year-end 2006 (prior to the crisis), year-end 2007 (early stages of the crisis) and year-ends 2008, 2009 and 2010 (height of the crisis). I expect that the differences may be more pronounced further into the crisis and closer to the response events, the majority of which occurred in 2008 to 2010 (see Table 2). Those measures that differ prior to the response event may suggest potentially useful leading

[14] This measure is known as the 'efficiency' ratio in the standard financial ratio analysis of banking.

[15] One could argue that this ratio could, in fact, be inversely associated with the likelihood of needing a more intensive response to the extent that liquid assets provide a useful secondary source of liquidity which building societies could tap in the event of funding shortfalls. On the other hand, there are potential opportunity costs of holding higher proportions of liquid assets which could weigh on earnings performance and, therefore, contribute to a need for more intensive actions.

indicators of financial vulnerability under a regulatory regime similar to that which existed prior to the crisis.

Tables 4 and 4A report summary statistics and mean comparison tests for the full sample period. The mean comparison tests evaluate whether the average CAMEL attributes differ between institutions that responded more intensively and those that did not during the run-up to and height of the financial crisis. Table 4A shows that, on average, institutions that responded more intensively had lower capital ratios, different asset quality measures (although the differences send somewhat mixed signals), less efficient management teams, and unfavourable earnings performance measures. The two liquidity measures also appear to differ between response intensities.

Table 5 provides a better sense of how these differences evolved over the crisis. In particular, this table reports the CAMEL attributes that were statistically significantly different (at the ten percent level or better) between response type at each year-end 2006 to 2009. Both the tier 1 leverage and risk-based capital ratios were significantly lower at firms that responded more intensively leading up to and during the height of the crisis.[16] At the same time, however, the total risk-based capital ratios did not differ between response intensities. These findings are consistent with the idea that even before the start of the crisis, firms that ultimately were forced to take more intensive actions during the crisis were more vulnerable and less well positioned to withstand significant shocks to asset quality and deal with unexpected losses. They also give an initial sense for how well risk-based measures foreshadowed potential firm-level vulnerability under the previous set of prudential regulations. It is interesting to note that further into the crisis the differences for the tier 1 risk-based measure became less apparent. Also of note, the table shows that firms that responded more intensively had *significantly lower leverage ratios* before the start of the crisis, despite reporting total risk-based capital ratios that were on average not significantly different from those that took less intensive actions to deal with the onset of the crisis.

The results suggest that during the earlier period and onset of the crisis, those building societies that eventually had to take more intensive actions had, on average, lower leverage ratios, inefficient management and weaker earnings. Such weaknesses became more apparent as the crisis unfolded and conditions worsened. These results provide initial clues about the potential shortcomings in the previous regulatory regime and offer ideas for improvement.

4 Methodology

While these univariate analyses are useful for identifying potential shortcomings in the previous regime, they fail to consider how the financial attributes as a group may have affected the likelihood of response intensity and bank behaviour more broadly under the previous regime. As a result, univariate analyses fail to consider how such variables may interact to influence a firm's overall vulnerability to financial stresses. This approach, for example, could possibly overlook important interactions that play a critical role in

[16] As discussed below, the relatively high correlation between the tier 1 leverage and tier 1 risk-based capital ratios prior to the implementation of the more risk-sensitive Basel II capital framework in 2007 approaches may partially explain this finding.

affecting financial fragility, possibly characterizing weaknesses in the previous regime incorrectly.
A more sophisticated econometric method that accounts for all attributes taken together may help overcome this problem and reduce misclassification rates.

To examine the effect of various financial indicators on response intensity, I use two separate and distinct approaches, each of which relies on the logistic probability model and maximum likelihood estimation. Under the first approach, referred to as 'single-period models', I use financial data at one point in time, e.g., December 31, 2005, to explain subsequent responses that occur from the financial data date to the end of 2011. The dependent variable in this approach, Y_s, is a dummy variable that equals one if building society *s* responded 'more intensively' at any time during the period from year-end 2005 to year-end 2011. I estimate the probability of a 'more intensive' response as a function of explanatory variables $X_{s,2005}$ measured at year-end 2005. If I assume that $F(\beta' X_{s,2005})$ is the cumulative logistic distribution function evaluated at $\beta' X_{s,2005}$, where β is a conforming vector of coefficients to be estimated, then the likelihood function of the model is:

$$Log\ L = \sum_s \{Y_s \log[F(\beta' X_{s,2005})] + (1-Y_s)\log[1-F(\beta' X_{s,2005})]\}, \qquad (1)$$

where s = 1 to n is the number of building societies.

I can also express the logistic model as the log odds ratio,

$$\log\, [P_s / (1-P_s)] = \beta_0 + \sum_k \beta_k' X_{k,s,2005}\,, \qquad (2)$$

where $P_s = Prob(Y_s = 1 \,|\, X_{s,2005})$ is the probability that building society *s* will have to undertake a more intensive response some time during the period spanning the financial data date, i.e., year-end 2005, and the end of 2011, given a vector of *K* explanatory variables.

I roll the window of time forward by one year progressively from 2005 to 2010 to evaluate whether data at the end of each year (2006 to 2010) are useful in explaining response intensity (that arises subsequent to the data date and through the end of 2011). This setup means that I will actually estimate six different models (i.e., one each based on financial data at each year-end 2005 to 2010), with each estimating the likelihood of needing a more intensive response over gradually shorter windows of time. In this regard, the approach is similar to that employed by previous researchers who use data from one point in time to explain bank failures over a window of time after the data date (e.g., see Whalen (1991) and Cole et al. (1995) and Cole and Wu (2009)). In addition, because the majority of the more intensive responses in the sample occur after mid-2008, this approach provides another way of examining how useful past financial data (e.g., from before the start of the crisis) are in explaining this type of response and therefore characterizing vulnerability more broadly. Univariate results reported in Tables 4 and 5 suggest that financial data from the distant past may, in fact, not be very helpful in explaining vulnerability to stress.

The second approach, referred to as "multi-period models", effectively pools the data (across firms and over quarters) and uses financial data from all quarters in evaluating the characteristics of response intensity. The approach allows for time-variation in the explanatory variables and treats a building society's condition as a function of its latest financial measures.[17] Because I use financial data over all quarters spanning the sample period rather than from just one point in time during the sample period, I modify the dependent and explanatory variables in the above specification so that they depend on time. In particular, I let $Y_{s,q}$ denote a dummy variable equal to one when building society s takes a more intensive response in quarter q and zero otherwise, and I estimate the probability of response intensity as a function of explanatory variables at each quarter $X_{s,q}$. Again, in the setup, q is quarterly spanning December 31, 2005 to December 31, 2011, with the relevant log odds ratio expressed as follows:

$$log\ [P_{s,q} / (1-P_{s,q})] = \beta_0 + \sum_k \beta_k' X_{k,s,q}\,, \qquad (3)$$

where $P_{s,q} = Prob(Y_{s,q} = 1 \,|\, X_{s,q})$ is the probability that society s responds in a more intensive fashion in quarter q, given a vector of K explanatory variables measured at quarter q (i.e., contemporaneously). In this paper, equation (3) represents the primary model of the characteristics of response intensity (i.e., vulnerability to stress). To account for the possibility that individual society observations may be correlated, I use logistic models that are robust to heteroscedasticity.[18]

Equation (3) identifies a combination of factors that characterizes response intensity at the time of the response. As such, this specification addresses the following question: under the previous regulatory regime, what were the features of societies that took more intensive actions to deal with the crisis at the time of the response. While useful for understanding attributes of these firms, this specification is perhaps less useful for supervisory purposes, where it is more important to identify potential vulnerabilities with sufficient lead time so that appropriate corrective actions can be taken and that losses (e.g., due to failure) can be mitigated.[19] Therefore, to use the multi-period logistic approach for early warning purposes, I lag the explanatory variables. The specification with lags helps to address the following questions: (i) what did firms that were forced to take more intensive responses to the crisis look like at different points in time leading up to the point of response and (ii) were these features different from those exhibited by firms that took less intensive actions. The distance the variables are lagged is equivalent to the length of the forecast period. So, for example, a four (an eight) quarter lag means that the financial variables predict the likely response (and indirectly signal vulnerability) one year (two years) hence. In what follows, I examine the in-sample classification performance of several models using lags of one, two, three, four and eight quarters.

5 Results

This section reports the estimation results from a variety of single- and multi-period models of response intensity. This section also compares the in-sample classification

[17] See Shumway (2001) for more details on this approach and its use in explaining bankruptcy risk. Poghosyan and Cihak (2009) employ a similar approach to examine the determinants of bank distress in Europe, while Cole and Wu (2009) extend this approach to examine factors explaining US commercial bank failures during the banking crisis of the late 1980s and early 1990s.

[18] In particular, I used the clustered robust estimation option in Stata, and assume that the errors are independent within each building society. This option uses a variance-covariance matrix that is robust to clustering of errors at the firm level.

[19] In this setup, failure or closure is obviously the most intensive and potentially most costly (to external parties) form of response.

accuracy of models in the single-period versus multi-period approaches. In making these comparisons, I relied on examining the sign, significance and magnitude of the estimated coefficients, as well as the overall fit of the models (as suggested by the pseudo-R^2). I took this route because I cannot use conventional methods to assess the incremental contribution of a single-period model relative to a multi-period model, since the models can not be nested within each other given the different nature of their explanatory variables (i.e., time-invariant under the single-period model versus time-dependent under the multi-period model).

5.1 Single-period models

Tables 6 and 7 report separate single-period models based on data from each year-end 2005 (Model 1), 2006 (Model 2), 2007 (Model 3), 2008 (Model 4) and 2009 (Model 5). The baseline models reported in Table 6a include only the Tier 1 leverage ratio as an explanatory variable and provide an initial sense of how well this variable distinguishes between more intensive respondents (i.e., more vulnerable firms) and less intensive respondents (i.e., less vulnerable firms). For all models, the tier 1 leverage ratio is highly significant (at the 5 percent level or higher) in explaining response intensity. Consistent with expectations, the sign on the coefficient estimate is negative, suggesting that building societies with higher (i.e., better) leverage ratios were less likely to have resorted to more intensive actions to deal with stressful conditions. Interestingly, the variable is highly significant even in models conditioned on data from well before the start of the crisis and the period when most of the more intensive responses occurred (i.e., 2008-2010).

These findings provide some clues about the potential shortcomings of the previous regulatory regime and the benefits of a minimum leverage ratio requirement similar to that proposed in Basel III. They also support the proposals related to the use of a leverage measure as an indicator of financial vulnerability.[20] A closer examination of the in-sample classification accuracy measures across models, however, suggests that the relative strength of the leverage ratio as an early warning indicator is lower based on measures from the more distant past. In the sample, the majority of the more intensive response events occur at or shortly after the end of 2008, and Model 4, which uses data from year-end 2008, appears to be the most accurate according to the pseudo-R^2 metric.

As a robustness check, I extend the base models to include both the tier 1 and total risk-based capital ratios. Table 6b shows that, in general, the leverage ratio remains negatively associated with the likelihood of response intensity. The results provide some initial indications that the leverage ratio may be a useful metric for distinguishing firms that were more vulnerable to financial stress under the pre-crisis regulatory regime, but that its discriminating power drops off the farther in advance of distress it is measured. Again, given that most of the response events in the sample occur at or just after the end of 2008, it is not surprising that the model based on data from that time (Model 4b) has the best in-sample classification rate.

[20] The recent amendments to the Basel capital framework, set out in Basel III, include a non-risk-based, leverage ratio requirement, designed to supplement risk-based minimum capital requirements on credit institutions. Basel III mandates that banks must have equity capital of at least three percent of non-risk-weighted total assets, including off balance sheet items. See Basel Committee on Supervision (2011) for more detail.

To account for a host of other potential influences found useful in explaining bank fragility, I include proxies for asset quality, management skills, earnings performance and liquidity in the baseline models. Table 7 reports a set of simple CAMEL attributes models.[21] In each specification, the leverage ratio is statistically significant and negative (consistent with expectations) in each of the five models. The earnings metric, ROA, is also statistically significant in three cases, with the sign on the coefficient estimate indicating that building societies with higher (lower) earnings were less (more) likely to resort to more intensive actions when faced with stressful conditions.

The table also shows that the Wald chi-square statistics are significant for each specification, suggesting that the five variables, as a group, are useful in explaining response intensity in each model. And consistent with the specifications using fewer explanatory variables, the models based on data closer to the response (i.e., from 2008 and 2009) have the highest in-sample accuracy.

Whether including measures of asset quality, management capability, earnings performance and liquidity position adds incremental explanatory to the baseline models (that employ only the leverage ratio) can be evaluated by examining the significance level on these additional variables as well as comparing the likelihood ratios.[22] It is clear from the results that the earnings metric, ROA, which is statistically significant across all five specifications, plays a role in explaining response intensity. And when focusing on Model 4c, which uses 2008 data, I see that the other variables as a group also appear to have incremental explanatory power. In this case, the likelihood ratio test statistic for the test of the joint hypothesis that all omitted variables from the baseline model is 12.6. With five degrees of freedom, the probability under the null hypothesis of this or a larger value is under 5 percent, suggesting that the additional attributes, as a group, are incrementally useful in explaining response intensity.

These results confirm the value of the leverage ratio for characterizing response intensity and, therefore, potential vulnerability during the previous regulatory regime, even after controlling for other financial attributes affecting building societies. At least with respect to the recent crisis, the results raise some questions about whether risk-based capital ratios are useful in characterizing response intensity and signalling firm-level fragilities.[23] As a result, they provide some initial evidence supporting recent proposals on a minimum non-risk-based capital ratio, i.e., a leverage ratio requirement. This requirement aims to act as a check to the risk-based capital requirements and addresses the ability of individual deposit-takers to build-up destabilizing amounts of leverage within the financial system more broadly under a purely risk-based capital regime.

[21] In choosing these candidate variables, I reviewed the correlation among all variables within each CAMEL attribute and selected only those that were not significantly correlated and those that were considerably different based on univariate results.

[22] This comparison is made between the baseline (leverage only) model, which in this situation is the constrained model, and the expanded model using a full set of CAMEL attributes, the unconstrained model in this analysis. A significant difference between the likelihood ratios may suggest marginal explanatory power of the additional variables.

[23] This finding does not mean that risk-based measures will not be helpful indicators of financial fragility going forward, but at least with respect to the previous crisis and regulatory regime, they played a relatively more limited role in characterizing vulnerable firms. Obviously, this caveat would need to be kept in mind when considering a surveillance programme that incorporates measures of capital adequacy.

5.2 Multi-period (pooled) models

Since firms' financial conditions vary over time and with economic conditions, it may be important to allow for this aspect when modelling response intensity.[24] For this reason, this subsection discusses results from a second approach to estimation that utilizes explanatory variables pooled both across building societies as well as over time. This approach not only considers the evolving conditions of building societies and allows the explanatory variables to depend on time, but also acts as a robustness check on earlier results.

Table 8 reports results from seven separate and distinct multi-period (i.e., pooled) logit models, each estimated using a variance-covariance matrix robust to clustering of errors at the firm level. The first three specifications (Models 6, 7 and 8) separately examine the association between response intensity and each of the three unique measures of capital adequacy, while the fourth (Model 9) examines how all three capital measures as a group relate to response intensity under the previous regulatory regime. The final three specifications (Model 10, 11, 12) include capital ratios and a wider set of CAMEL attributes. These multi-period models differ from the single-period models, in that they use a much larger, time-series, cross-section panel data set spanning from year-end 2005 to year-end 2010, a period that excludes a leverage requirement. As a result, the data set is roughly 20 (i.e., five years at 4 quarters per year) times larger than that of the single-period models that include observations for just one point in time for all building societies. A key benefit of using more data is that this approach is likely to produce more efficient in-sample classification, which means that we may be more confident about estimation results.

The qualitative results with respect to the leverage ratio appear robust across all specifications including this variable (i.e., Model 6, 9 and 10). As Table 8 shows, the leverage ratio is statistically significant and negatively associated with the likelihood of response intensity in all specifications. These findings are consistent with the single-period model results and, again, indicate that a lower (higher) leverage ratio is associated with a higher (lower) likelihood needing more intensive actions to deal with an onset of financial stress.

Results from Model 7 and 8 suggest that the risk-based capital ratios, when evaluated separately, are also significant in characterizing response intensity. The results are consistent with the idea that firms with higher (lower) risk-based capital measures are less (more) likely to need more intensive actions to deal with the onset of financial stress. The lower goodness-of-fit measures for these models, however, suggest that the discriminatory power of risk-based measures is relatively weaker than that of the leverage ratio, which sheds light on a key shortcoming of the pre-crisis regulatory regime. Results from Model 9, which includes all three capital measures, offer further insight. In particular, the likelihood ratio test statistic for the test of the joint hypothesis that the omitted risk-based capital variables from the Model 6 is 0.058. With two degrees of freedom, the probability under the null hypothesis of this or a smaller value is well below

[24] Indeed, Shumway (2001) shows that multi-period logistic models that incorporate time-varying explanatory variables produce more consistent estimates than single-period models (i.e., those that rely on data from one point in time) for forecasting bankruptcy. In particular, he shows that discrete time hazard models in which a firm's financial condition is a function of its most recent financial measures and which are estimated using the logistic distribution are more precise.

5 per cent, indicating that the risk-based capital measures are not incrementally useful in explaining the intensity of responses taken during the crisis.

The leverage ratio remains significantly negative in Model 10, which considers an expanded set of CAMEL attributes. The coefficients on the other variables are also consistent with expectations. A positive (negative) sign indicates that an increase in the relevant variable is associated with an increase (decrease) in the likelihood that a more intensive response was needed to deal with stress. Not surprisingly, the earnings proxy, ROA, is negatively associated with response intensity, indicating that firms with weak (strong) earnings were more (less) likely to require more intensive actions to deal with stressful conditions, everything else constant. The proxy for management quality, the efficiency ratio, has a positive and statistically significant coefficient. This suggests that firms with management teams that were less efficient in generating income (i.e., they have higher, or worse, efficiency ratios) were more likely to require more intensive efforts to mitigate stress conditions. The coefficients on the arrears rate on secured mortgages and the ratio of loans to assets, both of which proxy for asset quality, are positive and consistent with priors. These signs indicate that, under the pre-crisis regime, firms with lower (higher) levels of arrears were less (more) likely to need more intensive actions to deal with the ensuing stress. Also, firms that had lower loan asset concentration ratios were less likely to need more intensive actions to deal with stress. Finally, the coefficient on the liquidity variable (liquid assets ratio) is positive. This model fits the data rather well, with the pseudo-R^2 approximating 0.51.

As another check on the relative strength of the non-risk-based leverage ratio in explaining response intensity under a regulatory regime that excludes a leverage requirement, I estimated two models with similar CAMEL attributes, but whose capital adequacy measures include risk-based ratios. Model 11 includes the tier 1 risk-based capital ratio, while Model 12 includes the total risk-based capital measure. Results show that the risk-based measures are statistically significant and negatively associated with response intensity. The negative association implies that, everything else constant, firms with higher (lower) risk-based measures were less (more) likely to need more intensive efforts to deal with the onset of stress. The overall fit of these risk-based models, however, is lower than that of the model with the leverage ratio. This provides further evidence of the leverage ratio's better ability to classify response intensity and recognize potential vulnerabilities in the previous regulatory environment.

As another way to examine the robustness of these results, I estimated a random effects model in which the intercept varies at the individual building society level. Table 9 reports the results for each random effects specification, which exploits the heterogeneity of baseline models at the individual society level. The standard deviation of the random intercept in these specifications is insignificant in all specifications, indicating that building societies are relatively homogeneous in terms of the baseline model (Model 10) after considering the CAMEL attributes. The results are qualitatively similar to those under the pooled logit approach.

In summary, the findings suggest a small set of six CAMEL attributes were effective in characterizing response intensity and, therefore in discerning possible vulnerabilities heading the previous economic downturn. The results indicate that, everything else constant, firms with higher (lower) leverage ratios and earnings measures were less (more) likely to need more intensive efforts to deal with the onset of stressful conditions.

On the other hand, those with higher (lower) arrears rates, loan concentrations, efficiency ratios and liquid asset ratios were more (less) likely to need to resort to more intensive efforts to deal with stress. The relationship between the liquid assets ratio and response intensity is somewhat counterintuitive, but it may partly reflect that the more intensive respondents in the sample were relatively less efficient in their balance sheet management practices and thus in their management of net interest margins.

5.3 Early-warning use

While these results demonstrate the value of certain CAMEL factors in characterizing response intensity (and potential vulnerability), they are of limited use in providing early indications of problems within the building society sector. Early indication is critical to ensure sufficient time is available to undertake corrective actions or to mitigate losses that may arise from the loss of vital deposit-taking services or from the outright failure of firms. To address this issue and facilitate a more forward-looking view, I modify the multi-period models by lagging the explanatory variables. The distance of the lagged explanatory variables represents the forward horizon underlying the model.

Table 10 reports five distinct models with forecasting horizons spanning one, two, three, four and eight quarters. Each specification uses those variables found significant in the baseline Model 10. Four results stand out. First, in all cases, the leverage ratio remains statistically significant and negative, corroborating the findings above that leverage is an important discriminator of response intensity and, therefore, useful indicator of financial vulnerability in a regulatory regime excluding a leverage requirement. Second, and not surprisingly, the classification accuracy declines the more distant in the past the CAMEL attributes are measured.[25] Third, in addition to leverage, earnings proxies (ROA and Efficiency) appear to be important leading indicators of vulnerability in such a regime. Finally, the mortgage arrears rate is an important leading indicator.

As another robustness check, I estimated each of the above models using a stepwise (backward selection) routine that first includes all variables and then progressively eliminates those variables that do not remain statistically significant (at the 10 percent level or better) as the model is re-estimated with gradually fewer (statistically significant) variables. Table 11 reports results and shows that in all models, the tier 1 leverage ratio remains significant, further illustrating the ability of this variable to differentiate unsound from sound firms in the pre-crisis regulatory regime. Not surprisingly, the results from the model which has a forecast horizon of one quarter are similar to those produced from Model 10 based on contemporaneous financial attributes. In addition, the in-sample classification performance diminishes the further in the past the explanatory variables are measured.

5.4 Classification criterion

This subsection reviews the ability of the baseline multi-period model to attribute firms into one of the two response categories, less intensive and more intensive, as a way of calibrating criteria for classifying vulnerable firms in general. A key feature of the multi-period model is that it can be assessed in terms of its precision and, in particular, in

[25] I did not examine the rate at which classification accuracy declines, but simple inspection suggests that the decline may in fact increase with the length of the lag.

minimizing Type I and Type II error rates. A Type I error occurs when the model fails to classify a potentially vulnerable (i.e., one that required more intensive efforts to deal with stress during the crisis) society correctly, while a Type II error occurs when a less vulnerable (i.e., one that did not require more intensive efforts to deal with stress during the crisis) is incorrectly classified as vulnerable. In the context of this study, I classified all firms according to the following rule: vulnerable (not-vulnerable) if their likelihood of needing a more intensive response were above (below) a given cutoff level.

I reviewed the Type I versus Type II error tradeoffs to get a better sense of where a reasonable cutoff point might lie. Higher cutoff points result in lower Type II errors; however, these higher levels also increase the Type I errors. The optimal cutoff point will ultimately depend on the relative risk aversion of model users and how much weight they place on Type I and Type II errors. From a prudential perspective, there may be a strong case for placing more weight on Type I errors, since this approach could help avoid missing vulnerable firms and reduce costs associated with these cases.[26]

I reviewed the relationship between model classifications and actual response types for the baseline contemporaneous risk model (Model 10) using several different cutoff points. Figure 4 illustrates the trade-offs and clearly shows that at a cutoff probability point of around 2%, the model correctly classifies almost all cases involving more intensive response, while not classifying an inordinate proportion (i.e., only slightly over 5%) of firms as needing more-intensive actions. This 2% threshold provides a reasonable criterion for classifying building societies. To put this into context given the size of the UK building society sector, this means that only about three firms would be misclassified as vulnerable using this 2% threshold. Obviously, this approach assumes that the characterization of response intensity derived from the recent crisis and under the regulatory regime that was in place at the time holds going forward.[27]

6 Implications for policy and off-site monitoring

This section briefly discusses why this study’s framework and results may be of interest to regulators responsible for protecting and enhancing individual deposit-takers and the wider financial system. The study’s framework suggests that a small set of CAMEL attributes derived from routinely collected regulatory return data effectively characterized deposit-takers that, in the pre-crisis regulatory regime, had less capacity to deal with the onset of economic stress without relying on more intensive actions. Knowing which firms, and the extent to which the financial sector overall, exhibit features similar to those that were more susceptible to economic stresses in the past could help regulators in directing scarce supervisory resources or in shaping policy actions to reduce these vulnerabilities and their likely effects on the real economy.

[26] Such costs could include losses to the real economy that could arise, for example, from the reduction in critical lending and deposit-taking services and, in the extreme, to taxpayers from the failure of such firms.
[27] To put this into context given the size of the UK building society sector, this means that only about three firms would be misclassified as vulnerable using this 2% cutoff. Obviously, this approach assumes that the characterization of response intensity derived from the recent crisis holds going forward. Further, given the limited number of more intensive responses, it was not possible to undertake out-of-sample classification tests. This is a key caveat of this study that should be kept in mind when considering implications of these results for off-site monitoring.

This study also provides evidence on the significance of capital adequacy in characterizing vulnerability. This may be of interest to macroprudential policymakers responsible for identifying possible threats to real economic activity. Empirical evidence shows that relatively lower capitalized banks are more likely to restrict lending during a downturn. This trait can amplify the severity and duration of economic cycles. Gambacorta and Marques-Ibanez (2011), for example, show that banks with weaker core capital positions restricted loan supply more strongly during the crisis period. Carlson et al. (2011) use a novel data set of US bank information to control for loan demand and show that the relationship between lending and capital ratios was insignificant during benign economic periods but became significant during the recent financial crisis. Their results suggest that banks with low capital tended to restrict lending much more than those with higher capital ratios during the crisis. Berger and Bouwman (2009) also rely on US bank data and show that higher capital ratios help banks (of all sizes) increase their probability of survival, market share and profitability during crises, all of which help facilitate lending. This evidence supports the recent proposals to introduce a firm-level leverage ratio and reporting requirement.[28]

The framework in this paper can be used to get an initial sense of the first-order benefits of a leverage ratio requirement. Model 10 allows us to look at how the likelihood of needing more intensive responses – and, therefore, vulnerability to economic stress – changes given changes in leverage.[29] Figure 5 shows how this probability varies for an average firm at progressively higher leverage ratios. The figure also demonstrates that the incremental benefits decline considerably beyond the 3% level. Figure 5A provides a more granular snapshot of these marginal effects and indicates that increasing leverage from 3% to 5% can reduce the likelihood of needing a more intensive response by roughly 4 percentage points for the average firm.[30]

It is important to note that this analysis reflects only first-order effects and does not consider second-order effects associated with imposing and altering a leverage requirement. These second-order effects are likely to be significant and could include, for example, a shift in firms' risk-taking behaviour and strategic balance sheet restructuring in response to higher leverage requirements. The extent of these effects will depend on the degree to which institutions are bound by such higher requirements or a desire to maintain targeted capital buffers over and above the regulatory minimum. There is empirical evidence that firms' capital and balance sheet management practices are consistent with the idea that they desire to maintain targeted buffers as a way of avoiding costly regulatory interventions or sanctions associated with regulatory breach. In particular, research shows that changes in risk-based capital requirements affect banks and building societies' capital and balance sheet management practices (see, for example, Alfon et al. (2004) and Francis and Osborne (2010)). Additional empirical work has shown that one way in which banks achieve this result is by reigning in their lending activity, which can have negative implications for the real economy, especially if a sufficient number of institutions undertake similar strategic responses at the same time (see, for example, de-Ramon et al. (2012)). While I do not have empirical background on how banks and building societies respond to non-risk-based capital requirements, if the

[28] See, for example, BCBS 2011.
[29] In undertaking this analysis, I set the values for all other financial variables at the sector average (based on 2011 data) and computed the probability that more intensive response will be needed of over a plausible range of leverage ratios.
[30] Similar analyses for other variables in Model 10 are available upon request.

incentives to avoid regulatory costs under a regime that includes a leverage ratio minimum hold, then these may also affect lending behaviour, with further implications for economic growth.

Supervisors may find the information from these reduced-form models helpful in informing judgments about firm-specific risks and broader sector risks. The output represents a summary statistic of firm-level vulnerability (i.e., probability of response intensity) based on several measures derived from routinely filed regulatory returns. All firms in the sector could then be ranked using these summary statistics. For micro-prudential purposes, such rankings can provide supervisors with a quick snapshot of relative vulnerabilities, and the underlying contributors, within this sector. This snapshot can help in focusing on-site and off-site reviews, as well as in directing scarce supervisory resources. Also, because these rankings can help identify firms that have less capacity to deal with the onset of financial difficulties, they could prove useful for contextualizing and assessing the efficacy of firms' recovery plans. Supervisors may, for example, want to raise more questions about these plans or ask for more detailed information from firms if a firm exhibits traits similar to those of firms that were forced to undertake more intensive measures during the crisis.

For macroprudential purposes, the results may give policymakers at least an initial sense of sector resilience. For instance, there may be concerns when results show a significant proportion of firms with high probabilities or high probabilities at a few firms with well-established connections (e.g., through interbank borrowing arrangements) with a number of low-risk building societies or commercial banks. Aggregating probabilities across firms (e.g., simple or asset-weighted average of response probabilities) and monitoring these over time may also provide another view of sector resilience. Finally, monitoring how the distribution of more intensive response probabilities changes over time can also shed light on emerging trends and issues that may be of concern to supervisors.

It must be kept in mind, however, that a key caveat limiting this study's results for off-site supervisory purposes is that the results reflect behaviour under the pre-crisis regulatory regime, which, as a result, may differ notably from behaviour under the revisions of Basel III. Since the new regime will include a leverage requirement, it is not unreasonable to expect that this mandate may alter deposit-takers' capital and balance sheet management practices. If significant behavioural shifts occur, then this means that the financial profiling relationships discussed in this paper may not necessarily be effective in characterizing firm-level weaknesses under the updated regulatory regime.

7 Conclusions and future research

The financial crisis had a substantial impact on the UK banking system, as firms undertook a host of costly responses to deal with the downturn in economic conditions. These responses varied considerably across firms. Some firms made less intensive changes to business models and capital and balance sheet management practices, while others resorted to more intensive actions (i.e., debt-equity swaps, mergers with/acquisitions by stronger peers and outright closure) to deal with the onset of financial difficulties. This study examines the extent to which the underlying financial condition, both before and at the height of the crisis, of firms that ultimately relied on more intensive measures differed from those that did not.

The study presents a model for profiling financial vulnerability that could also be used to highlight individual firms that are more likely to require more intensive actions (and therefore have less capacity) to deal with stresses similar to those experienced in the recent crisis. It focused on a particular subset of UK deposit-takers (i.e., building societies) that are similarly restricted in their ability to access external capital. This focus better isolates the effects of financial condition on response intensity compared with a setup using all deposit-takers. Evaluating the drivers of response choice and characteristics of vulnerability in the wider banking industry is an area for future research.

It should be noted, however, that the approach and the results discussed in this study come with a key caveat which limits their use in profiling risk going forward. In particular, this paper's results reflect bank behaviour under a pre-crisis regulatory regime (e.g., Basel I and Basel II), which is notably different from the revisions recently introduced under Basel III. This difference is especially true with respect to capital requirements, which under the new regime includes a leverage requirement. As a result, the influence of the financial measures that played a role in explaining deposit-takers' response intensity during the crisis and discussed above may differ under the revised regime if firms change behaviour in response. Still, the results from this paper are useful for highlighting possible weaknesses of the previous regime and for providing a better understanding of the reasons underlying the revisions in Basel III.

I find that, under the previous regulatory regime, firms that were less capitalized (as measured by non-risk-based leverage and risk-based ratios), had worse asset quality, employed less efficient management teams, and reported lower earnings ultimately required more intensive actions to deal with the onset of financial difficulty during the crisis. I also find that, under the previous regime, a simple leverage (i.e., capital to assets) ratio performed better than risk-based ratios in distinguishing response intensity and potential vulnerabilities. This finding supports the recent regulatory emphasis on non-risk-based capital ratios to assist in addressing problems that contributed to the crisis and that are not adequately tackled by risk-based measures alone.

A useful feature of the modelling approach discussed in this paper is its objective consideration of a broad set of financial (CAMEL) attributes and their interactions in profiling firm-level vulnerability. This approach means, for example, that low capital ratios would not be the sole criterion for triggering heightened supervisory attention. Rather, concerns about vulnerability would be based on the attributes as a group and their relative importance in explaining how firms responded to previous economic downturns. The output from the approach could complement regular stress-testing efforts and assist in evaluating firms' recovery plans by pointing to firms that may be less capable of dealing with the onset of adverse economic conditions. Using the output in this fashion, however, requires a careful consideration and better understanding of how firms may alter business models, capital and balance sheet management practices under the new regulatory regime which includes a leverage requirement.

There are a few extensions of this study that could help in that direction. First, developing a similar model using data from the UK banking sector and evaluating whether the characteristics of vulnerability differ between banks and building societies are two important extensions. Second, the influence of macroeconomic variables in characterizing vulnerability needs further exploration. The multi-period (pooled) modelling approach makes this extension tractable. Third, refining the definition of response intensity to include a finer breakdown of actions (e.g., merger, bail-in, failure) that vary according to the degree of supervisory concern or economic costs and isolating the determinants of these more granular actions using multinomial models may further help in focusing supervisory resources and in spotting potential vulnerabilities with more severe consequences for the economy. Fourth, undertaking formal, out-of-sample Type I and II error testing using similar data on how UK firms responded to financial difficulties under the revised regime would help in understanding the merits of using reduced-form models for risk profiling purposes more generally. Finally, evaluating how financial institutions altered capital, balance sheet and risk-taking practices in response to a leverage requirement in other countries where such a mandate already exists (e.g., United States) may provide some clues about behaviours in the UK under similar regulatory constraints.

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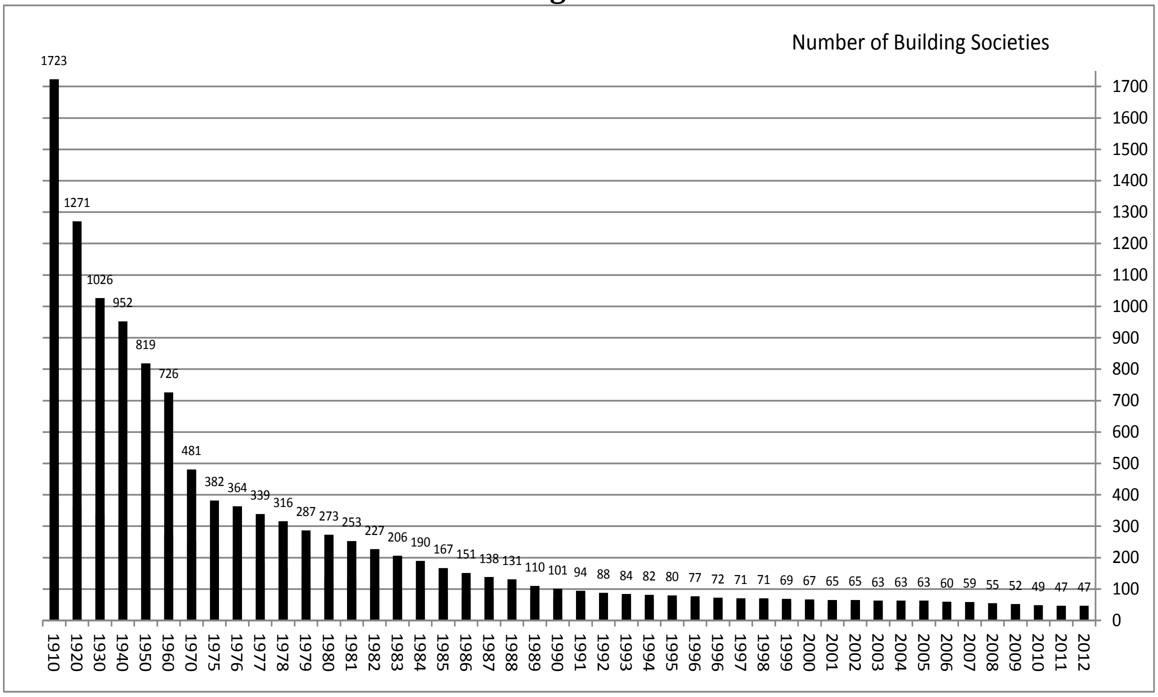
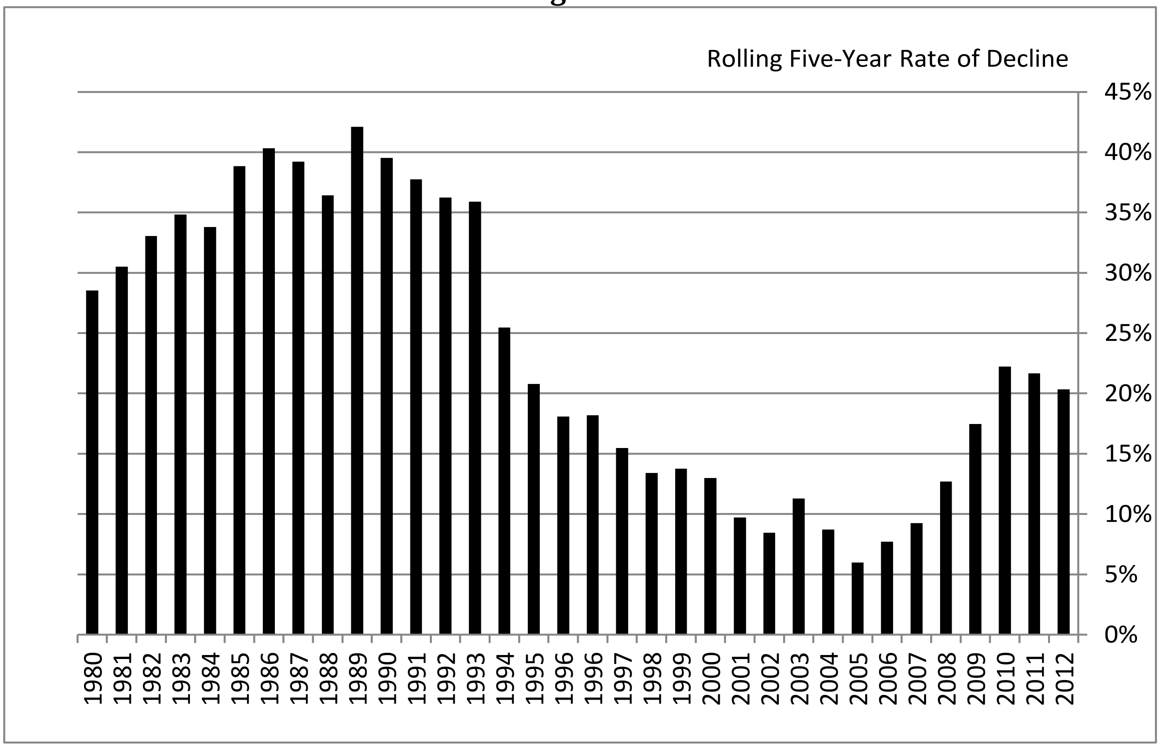
Figure 1



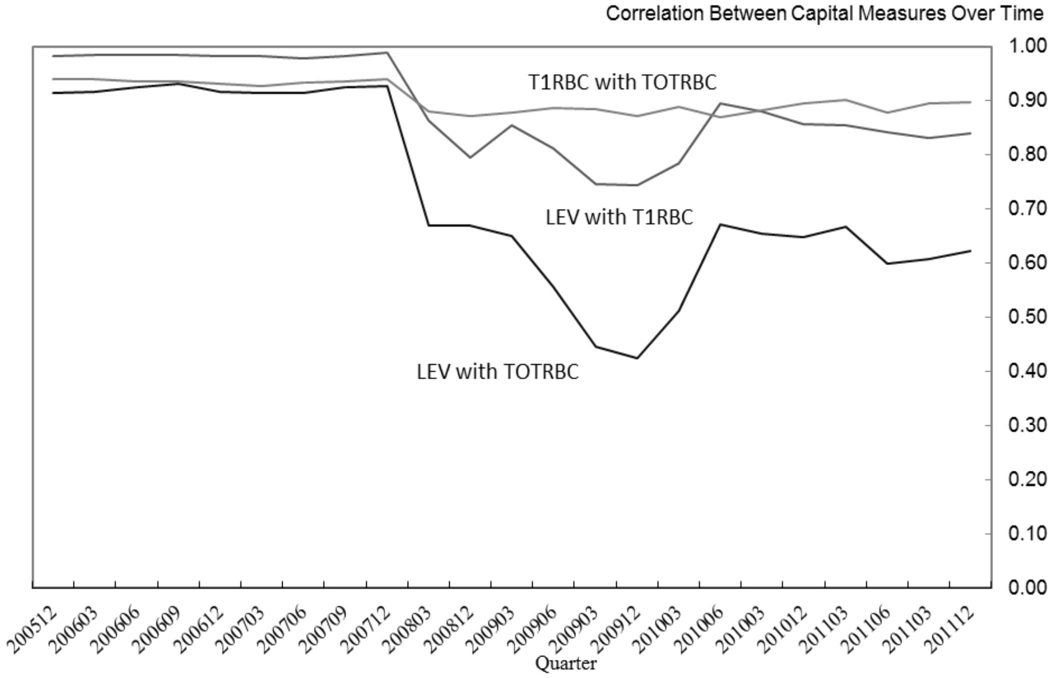
Source: UK Building Societies Association.

Figure 2



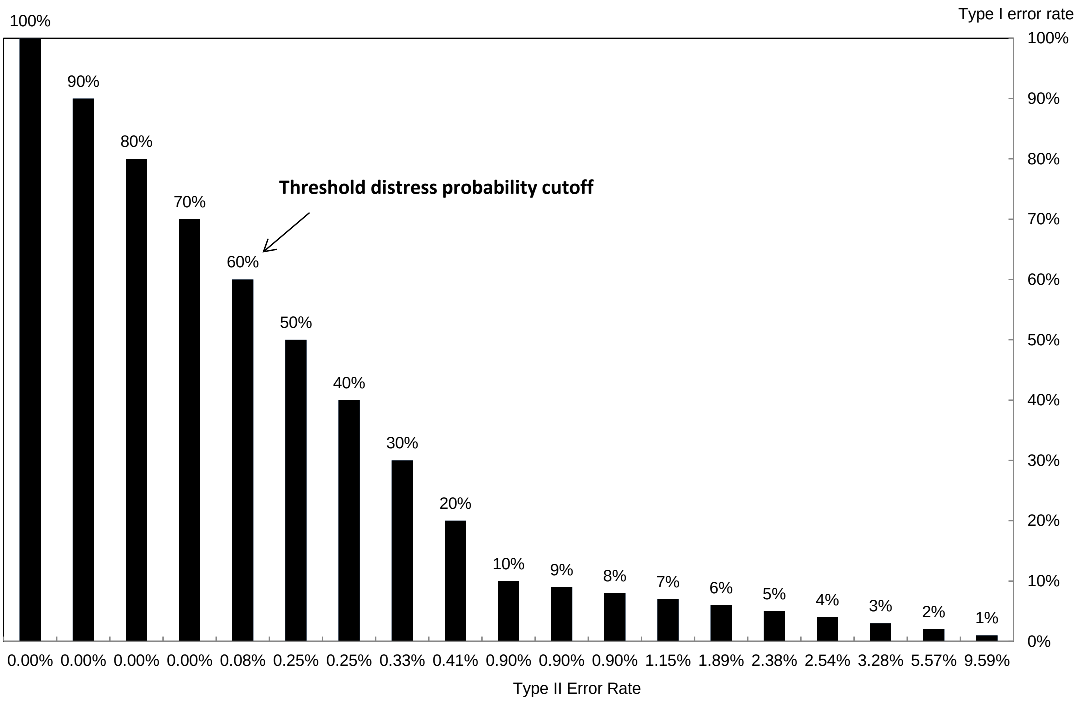
Source: UK Building Societies Association and author's calculation.

Figure 3



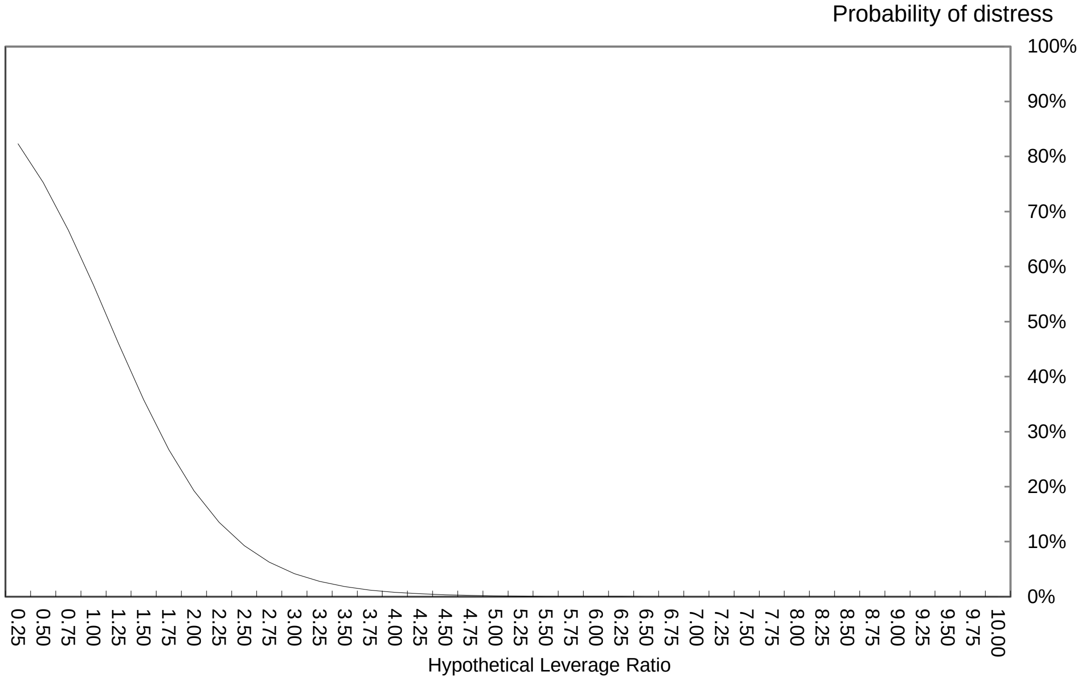
Source: FSA regulatory data and author's calculations.

Figure 4



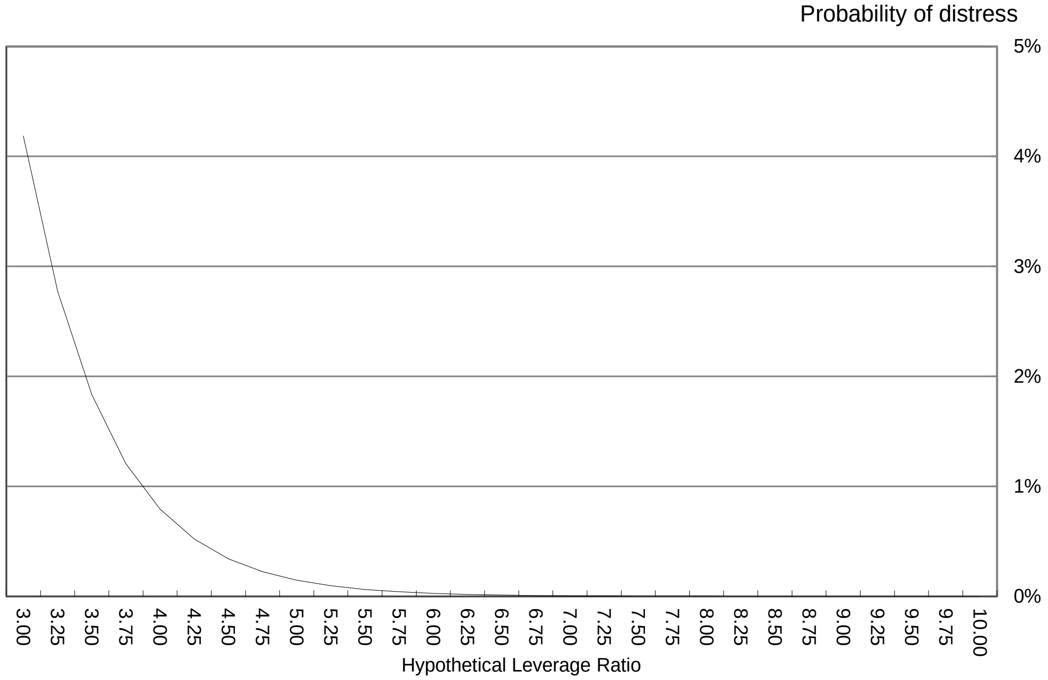
Source: Author's calculations.

Figure 5
Marginal Effects of Leverage
(Using Data as of Year-end 2011)



Source: FSA regulatory return data and author's calculations.

Figure 5a



Source: FSA regulatory return data and author's calculations.

Table 1
UK Building Society More Intensive Response Events
(20071231 to 20111231)

Financial Statement Quarter-end[a]	Response Quarter	Number	Cumulative Percent	Number	Cumulative Percent
20071231		0	0.00%	0	0.00%
20080331		0	0.00%	0	0.00%
20080630		0	0.00%	0	0.00%
20080930	20080930	1	8.33%	1	8.33%
20081231	20081231	4	33.33%	5	41.67%
20090331	20090331	1	8.33%	6	50.00%
20090630	20090630	2	16.66%	8	66.67%
20090930					
20091231	20091231	1	8.33%	9	75.00%
20100331					
20100630	20100630	1	8.33%	10	83.33%
20100930	20100930	1	8.33%	11	91.67%
20101231					
20110331					
20110630					
20110930	20110930	1	8.33%	12	100.00%
20111231					

Source: KPMG Building Society annual database, FSA database and discussion with FSA supervisors.

Table 2
Evolution of More Intensive versus Less Intensive Building Society Reponses

This table reports the distribution of more intensive versus less intensive responses to the financial crisis over the quarters spanning December 31, 2005 to December 31, 2011.

Financial Statement Quarter-end[a]	Number More Intensive[b]	Number Less Intensive	Total	Percentage More	Less	Total
20051231	12	46	58	20.7	79.3	100.00
20060331	12	46	58	20.7	79.3	100.00
20060630	12	46	58	20.7	79.3	100.00
20060930	12	46	58	20.7	79.3	100.00
20061231	12	46	58	20.7	79.3	100.00
20070331	12	46	58	20.7	79.3	100.00
20070630	12	46	58	20.7	79.3	100.00
20070930	12	46	58	20.7	79.3	100.00
20071231	12	46	58	20.7	79.3	100.00
20080331	12	46	58	20.7	79.3	100.00
20080630	12	46	58	20.7	79.3	100.00
20080930	12	46	58	20.7	79.3	100.00
20081231	10	46	56	17.9	82.1	100.00
20090331	8	46	54	14.8	85.2	100.00
20090630	7	47	54	13.0	87.0	100.00
20090930	5	46	51	9.8	90.2	100.00
20091231	5	46	51	9.8	90.2	100.00
20100331	5	45	50	10.0	90.0	100.00
20100630	4	47	51	7.8	92.2	100.00
20100930	3	46	49	6.1	93.9	100.00
20101231	2	46	48	4.2	95.8	100.00
20110331	2	45	47	4.3	95.7	100.00
20110630	2	47	49	4.1	95.9	100.00
20110930	2	46	48	4.2	95.8	100.00
20111231	1	46	47	2.1	97.9	100.00
Total Society-Qtr Observations	200	1151	1351	14.8	85.2	100.00

[a] Regulatory report date.
[b] Reflects the number of more intensive response events that occurred subsequent to the financial statement quarter-end date through December 31, 2011.

Table 3
Definition of Variables Used in Explaining Response Intensity

Variable	Definition	Expected Association with Response Intensity
Capital Adequacy (3)		
Tier 1 Leverage Ratio (T1LEV)	Tier 1 capital as a percentage of total assets	-
Tier 1 Risk-Based Ratio (T1RBC)	Tier 1 capital as a percentage of risk-weighted assets	-
Total Risk-Based Ratio (TOTRBC)	Total risk-based capital as a percentage of risk-weighted assets	-
Asset Quality (9)		
1st Mortgage Arrears % (ARFSRP_I)	Total arrears on residential real estate loans to individuals as a percentage of such loans	+
Other Mortgage Arrears % (ARFSRP_O)	Total arrears on residential real estate loans to others as a percentage of such loans	+
Other Arrears on Loans to Individuals % (AROTHR_I)	Total arrears on partially/unsecured loans to individuals as a percentage of such loans	+
Other Arrears on Other Loans % (AROTHR_O)	Total arrears on partially/unsecured loans to others as a percentage of such loans	+
Repossessed loans to total assets (REPOSSES)	Total repossessed loans as a percentage of total loans	+
Provision coverage % (PROV_ARS)	Total loan loss provisions as a percentage of total arrears	-
Provisions to total loans (PROV_LNS)	Total loan loss provisions as a percentage of total loans	+
Total loans to assets (LNS_ASST)	Total loans as a percentage of assets	+/-
Risk-weighted assets to total assets (RWA_ASST)	Total risk-weighted assets as a percentage of total assets	+
Management (5)		
Efficiency (cost to income) ratio (EFF_NCY)	Total non-interest cost to income ratio	+
Residential real estate concentration (RESRE_TA)	Total residential real estate loans as a percentage of total assets	+/-
Other secured loans (OTH_FSOL)	Total other fully-secured by land loans as a percentage of total assets	+/-
Real estate development loans (DEVEL_TA)	Total real estate development loans as a percentage of total assets	+/-
Size indicator	Natural log of total assets	+/-
Earnings Performance (2)		
Return on Average Assets (ROA)	Annualized net income after tax divided by average assets (2 quarter average)	-
Return on Average Equity (ROE)	Annualized net income after tax divided by average equity (2 quarter average)	-
Liquidity (2)		
Liquid assets proportion (LIQ_ASST)	Liquid assets (as defined per regulation) as a percentage of total assets	+/-
Loans to deposits (LNS_DEP)	Total loans as a percentage of total deposits	+

Table 4
Summary Statistics Full Sample

CAMEL Proxy (Number of Variables)	Observations	Mean	Standard Deviation	Minimum	Maximum
Capital Adequacy (3)					
Tier 1 Leverage Ratio (T1LEV)	1241	5.98	1.82	0	12.82
Tier 1 Risk-Based Ratio (T1RBC)	1242	14.41	4.73	0	33.27
Total Risk-Based Ratio (TOTRBC)	1242	16.09	4.21	3.65	37.51
Asset Quality (9)					
1st Mortgage Arrears % (ARFSRP_I)	1277	1.49	2.57	0	23.83
Other Mortgage Arrears % (ARFSRP_O)	1040	6.6	39.13	0	624
Other Arrears on Loans to Individuals % (AROTHR_I)	270	11.44	20.95	0	129.42
Other Arrears on Other Loans % (AROTHR_O)	740	0.61	5.34	0	100
Repossessed loans to total assets (REPOSSES)	1237	0.05	0.2	0	2.09
Provision coverage % (PROV_ARRS)	1165	42.33	183.91	0	4180.5
Provisions to total loans (PROV_LNS)	1333	0.21	0.28	0	3.91
Total loans to assets (LNS_ASST)	1295	74.64	4.8	54.13	86.4
Risk-weighted assets to total assets (RWA_ASST)	1241	42.06	6.65	11.29	66.62
Management (5)					
Efficiency (cost to income) ratio (EFF_NCY)	1334	70.24	41.1	0	1078.43
Residential real estate concentration (RESRE_TA)	1260	67.85	8.69	0	83.36
Other secured loans (OTH_FSOL)	753	1.11	2.69	0	16.85
Real estate development loans (DEVEL_TA)	1237	8.31	188.54	0	66.31
Asset Size (£000s)	1295	666636	6	19732	207366849
Earnings Performance (2)					
Return on Average Assets (ROA)	1248	0.3	0.49	-10.95	3.5
Return on Average Equity (ROE)	1248	3.95	24.25	-820.59	81.04
Liquidity (2)					
Liquid assets proportion (LIQ_ASST)	1295	23.81	4.85	11.8	45.19
Loans to deposits (LNS_DEP)	1332	75.87	14.84	0	114.94

Source: FSA regulatory returns and author's calculation.

Table 4A
Mean Comparison Tests

CAMEL Proxy (Number of Variables)	Less Intensive Responses Observations	Mean	Standard Deviation	More Intensive Responses Observations	Mean	Standard Deviation	Mean t-test t	Probability
Capital Adequacy (3)								
Tier 1 Leverage Ratio (T1LEV)	1076	6.18	1.80	165	4.66	1.39	12.56	0.0000
Tier 1 Risk-Based Ratio (T1RBC)	1077	14.94	4.64	165	10.91	3.73	12.47	0.0000
Total Risk-Based Ratio (TOTRBC)	1077	16.43	4.33	165	13.88	2.41	11.11	0.0000
Asset Quality (9)								
1st Mortgage Arrears % (ARFSRP_I)	1102	1.56	2.70	175	1.12	1.46	3.22	0.0014
Other Mortgage Arrears % (ARFSRP_O)	905	4.87	25.80	135	18.17	85.02	-1.80	0.0734
Other Arrears on Loans to Individuals % (AROTHR_I)	210	12.77	22.99	60	6.79	9.94	2.93	0.0037
Other Arrears on Other Loans % (AROTHR_O)	633	0.70	5.77	107	0.09	0.41	2.62	0.0089
Repossessed loans to total assets (REPOSSES)	1073	0.05	0.19	164	0.09	0.27	-2.12	0.0353
Provision coverage % (PROV_ARRS)	1022	40.50	194.47	143	55.40	71.46	-1.75	0.0813
Provisions to total loans (PROV_LNS)	1146	0.22	0.24	187	0.20	0.47	0.45	0.6499
Total loans to assets (LNS_ASST)	1119	74.54	4.81	176	75.26	4.71	-1.89	0.0597
Risk-weighted assets to total assets (RWA_ASST)	1076	41.92	6.59	165	42.99	6.99	-1.84	0.0678
Management (5)								
Efficiency (cost to income) ratio (EFF_NCY)	1148	67.94	17.06	186	84.44	100.66	-2.23	0.0269
Residential real estate concentration (RESRE_TA)	1092	67.82	8.42	168	68.03	10.28	-0.25	0.8015
Other secured loans (OTH_FSOL)	686	1.10	2.73	67	1.30	2.33	-0.68	0.4999
Real estate development loans (DEVEL_TA)	1073	9.16	202.43	164	2.74	5.61	1.04	0.3008
Asset Size (log of total assets)	1119	13.20	1.73	176	14.75	1.73	-0.53	0.5950
Earnings Performance (2)								
Return on Average Assets (ROA)	1080	0.35	0.34	168	0.04	0.99	3.98	0.0001
Return on Average Equity (ROE)	1080	4.99	5.45	168	-2.76	64.40	1.60	0.1207
Liquidity (2)								
Liquid assets proportion (LIQ_ASST)	1119	24.02	4.90	176	22.47	4.33	4.33	0.0000
Loans to deposits (LNS_DEP)	1147	76.18	14.43	185	73.95	17.11	1.68	0.0943

Source: FSA and PRA regulatory returns and author's calculation. Grey shading highlights differences at the 10% level of better.

Table 5
Summary of Significant Differences Spanning the Crisis

This table reports the variables that were significantly different at the ten percent level or better between firms that took more intensive responses and those that took less intensive responses to the crisis. YES denotes those variables that were significantly different at the ten percent or better level.

CAMEL Proxy (Number of Variables)	200612	200712	200812	200912	% Times Significantly Different
Capital Adequacy (3)					
Tier 1 Leverage Ratio (T1LEV)	YES	YES	YES	YES	100%
Tier 1 Risk-Based Ratio (T1RBC)	YES	YES	YES	NO	75%
Total Risk-Based Ratio (TOTRBC)	NO	NO	NO	NO	0%
Asset Quality (9)					
1st Mortgage Arrears % (ARFSRP_I)	NO	NO	NO	NO	0%
Other Mortgage Arrears % (ARFSRP_O)	NO	NO	YES	NO	25%
Other Arrears on Loans to Individuals % (AROTHR_I)	NO	NO	NO	NO	0%
Other Arrears on Other Loans % (AROTHR_O)	YES	NO	NO	NO	25%
Repossessed loans to total assets (REPOSSES)	NO	YES	NO	NO	25%
Provision coverage % (PROV_ARRS)	YES	NO	NO	YES	50%
Provisions to total loans (PROV_LNS)	NO	NO	NO	NO	0%
Total loans to assets (LNS_ASST)	NO	NO	NO	NO	0%
Risk-weighted assets to total assets (RWA_ASST)	NO	NO	NO	NO	0%
Management (5)					
Efficiency (cost to income) ratio (EFF_NCY)	NO	YES	YES	NO	50%
Residential real estate concentration (RESRE_TA)	NO	NO	NO	NO	0%
Other secured loans (OTH_FSOL)	NO	NO	NO	NO	0%
Real estate development loans (DEVEL_TA)	NO	NO	NO	NO	0%
Asset Size (log of total assets)	NO	NO	NO	NO	0%
Earnings Performance (2)					
Return on Average Assets (ROA)	YES	YES	YES	YES	100%
Return on Average Equity (ROE)	NO	NO	YES	YES	50%
Liquidity (2)					
Liquid assets proportion (LIQ_ASST)	NO	NO	NO	NO	0%
Loans to deposits (LNS_DEP)	NO	NO	NO	NO	0%
Number of statistically significant differences	5	5	6	4	
At 1% significance level	4	0	1	0	
At 5% significance level	0	4	4	1	
At 10% significance level	1	1	1	3	
Percentage of statistically significant differences	24%	24%	29%	19%	

Source: Author's calculation.

.

Table 5A
Mean Comparison Tests
(at 200612)

	Less Intensive Responses			More Intensive Responses			Mean t-test	
CAMEL Proxy (Number of Variables)	Observations	Mean	Standard Deviation	Observations	Mean	Standard Deviation	t	Probability
Capital Adequacy (3)								
Tier 1 Leverage Ratio (T1LEV)	46	6.46	1.80	12	5.01	1.21	3.32	0.0028
Tier 1 Risk-Based Ratio (T1RBC)	46	13.68	3.98	12	10.62	2.93	2.97	0.0069
Total Risk-Based Ratio (TOTRBC)	46	14.84	3.62	12	13.47	2.43	1.55	0.1343
Asset Quality (9)								
1st Mortgage Arrears % (ARFSRP_I)	46	0.77	0.99	12	0.63	1.19	0.37	0.7154
Other Mortgage Arrears % (ARFSRP_O)	41	13.03	53.66	9	74.72	206.54	-0.89	0.3990
Other Arrears on Loans to Individuals % (AROTHR_I)	8	3.00	4.90	4	5.03	10.06	-0.38	0.7242
Other Arrears on Other Loans % (AROTHR_O)	10	0.00	0.00	6	0.00	0.00	2.62	0.0089
Repossessed loans to total assets (REPOSSES)	46	0.06	0.20	12	0.01	0.02	1.54	0.1310
Provision coverage % (PROV_ARRS)	46	41.15	40.00	12	94.31	85.08	-2.10	0.0565
Provisions to total loans (PROV_LNS)	46	0.16	0.11	12	0.17	0.08	-0.16	0.8762
Total loans to assets (LNS_ASST)	46	76.70	5.03	12	76.24	5.65	0.26	0.7987
Risk-weighted assets to total assets (RWA_ASST)	46	47.46	3.02	12	47.59	3.53	-0.12	0.9084
Management (5)								
Efficiency (cost to income) ratio (EFF_NCY)	46	66.67	10.89	12	69.22	9.40	-0.81	0.4297
Residential real estate concentration (RESRE_TA)	46	70.16	7.45	12	69.85	9.51	0.11	0.9166
Other secured loans (OTH_FSOL)	0	0.00	0.00	0	0.00	0.00	na	na
Real estate development loans (DEVEL_TA)	46	0.14	0.30	12	0.09	0.29	0.52	0.6107
Asset Size (log of total assets)	46	13.12	1.74	12	14.60	1.84	-0.37	0.7099
Earnings Performance (2)								
Return on Average Assets (ROA)	46	0.37	0.15	12	0.27	0.08	3.15	0.0033
Return on Average Equity (ROE)	46	6.23	3.31	12	5.71	1.88	0.71	0.4853
Liquidity (2)								
Liquid assets proportion (LIQ_ASST)	46	22.15	5.06	12	22.18	5.66	-0.02	0.9870
Loans to deposits (LNS_DEP)	46	83.16	5.27	12	82.17	5.72	0.55	0.5922

Source: FSA and PRA regulatory returns and author's calculation. Grey shading highlights differences at the 10% level of better.

Table 5B
Mean Comparison Tests
(at 200712)

CAMEL Proxy (Number of Variables)	Less Intensive Responses: Observations	Less Intensive Responses: Mean	Less Intensive Responses: Standard Deviation	More Intensive Responses: Observations	More Intensive Responses: Mean	More Intensive Responses: Standard Deviation	Mean t-test: t	Mean t-test: Probability
Capital Adequacy (3)								
Tier 1 Leverage Ratio (T1LEV)	38	6.39	1.80	8	5.17	1.08	2.56	0.0204
Tier 1 Risk-Based Ratio (T1RBC)	38	13.60	4.04	8	11.18	2.60	2.14	0.0486
Total Risk-Based Ratio (TOTRBC)	38	14.73	3.61	8	13.32	2.03	1.52	0.1436
Asset Quality (9)								
1st Mortgage Arrears % (ARFSRP_I)	46	0.45	0.86	12	0.24	0.75	0.83	0.4116
Other Mortgage Arrears % (ARFSRP_O)	40	3.34	14.91	9	0.00	0.01	1.41	0.1656
Other Arrears on Loans to Individuals % (AROTHR_I)	8	3.19	5.81	4	3.39	6.79	-0.05	0.9604
Other Arrears on Other Loans % (AROTHR_O)	8	0.00	0.00	5	0.00	0.00	na	na
Repossessed loans to total assets (REPOSSES)	38	0.04	0.11	8	0.00	0.00	2.25	0.0304
Provision coverage % (PROV_ARRS)	24	151.86	466.72	3	128.94	106.70	0.20	0.8425
Provisions to total loans (PROV_LNS)	46	0.16	0.12	12	0.16	0.09	0.06	0.9715
Total loans to assets (LNS_ASST)	38	74.90	5.05	8	74.19	3.71	0.46	0.6553
Risk-weighted assets to total assets (RWA_ASST)	38	47.35	3.38	8	46.48	2.57	0.82	0.4265
Management (5)								
Efficiency (cost to income) ratio (EFF_NCY)	46	64.53	10.59	12	71.40	11.19	-1.91	0.0731
Residential real estate concentration (RESRE_TA)	38	67.44	8.00	8	68.24	6.52	-0.30	0.7666
Other secured loans (OTH_FSOL)	0	0.00	0.00	0	0.00	0.00	na	na
Real estate development loans (DEVEL_TA)	38	0.09	0.15	8	0.10	0.29	-0.16	0.8780
Asset Size (log of total assets)	38	12.95	1.74	8	14.51	2.26	-0.08	0.9302
Earnings Performance (2)								
Return on Average Assets (ROA)	38	0.40	0.17	9	0.28	0.11	2.72	0.0134
Return on Average Equity (ROE)	38	6.83	4.03	9	5.25	2.38	1.54	0.1380
Liquidity (2)								
Liquid assets proportion (LIQ_ASST)	38	24.07	5.09	8	24.52	3.64	-0.29	0.7725
Loans to deposits (LNS_DEP)	46	81.18	4.88	12	80.28	3.96	0.67	0.5120

Source: FSA and PRA regulatory returns and author's calculation. Grey shading highlights differences at the 10% level of better.

Table 5C
Mean Comparison Tests
(at 200812)

	Less Intensive Responses			More Intensive Responses			Mean t-test	
CAMEL Proxy (Number of Variables)	Observations	Mean	Standard Deviation	Observations	Mean	Standard Deviation	t	Probability
Capital Adequacy (3)								
Tier 1 Leverage Ratio (T1LEV)	45	5.76	1.74	10	3.71	0.88	2.83	0.0000
Tier 1 Risk-Based Ratio (T1RBC)	46	14.58	4.87	10	10.13	5.28	2.45	0.0298
Total Risk-Based Ratio (TOTRBC)	46	16.14	4.86	10	14.09	3.18	1.66	0.1123
Asset Quality (9)								
1st Mortgage Arrears % (ARFSRP_I)	45	2.03	3.05	10	2.09	1.13	-0.09	0.9247
Other Mortgage Arrears % (ARFSRP_O)	31	1.30	3.26	7	0.19	0.45	1.83	0.0765
Other Arrears on Loans to Individuals % (AROTHR_I)	7	9.30	10.80	3	2.22	3.84	1.52	0.1658
Other Arrears on Other Loans % (AROTHR_O)	31	4.12	18.01	7	0.24	0.41	1.20	0.2392
Repossessed loans to total assets (REPOSSES)	44	0.06	0.32	10	0.11	0.31	-0.50	0.6230
Provision coverage % (PROV_ARRS)	44	15.96	20.27	10	8.58	21.31	1.00	0.3367
Provisions to total loans (PROV_LNS)	45	0.17	0.17	10	0.10	0.18	1.14	0.2770
Total loans to assets (LNS_ASST)	45	73.61	3.09	10	74.62	4.16	-0.72	0.4837
Risk-weighted assets to total assets (RWA_ASST)	45	40.20	6.63	10	36.35	7.47	1.50	0.1581
Management (5)								
Efficiency (cost to income) ratio (EFF_NCY)	46	67.44	12.30	10	80.15	14.98	-2.51	0.0280
Residential real estate concentration (RESRE_TA)	44	66.93	7.96	10	67.72	12.08	-0.19	0.8463
Other secured loans (OTH_FSOL)	43	1.40	3.47	10	0.87	2.25	0.60	0.5552
Real estate development loans (DEVEL_TA)	44	4.80	6.10	10	5.20	8.39	-0.14	0.8880
Asset Size (log of total assets)	45	13.35	1.75	10	14.62	2.02	-0.13	0.9004
Earnings Performance (2)								
Return on Average Assets (ROA)	45	0.12	0.53	10	-0.58	0.89	2.39	0.0372
Return on Average Equity (ROE)	45	1.22	7.77	10	-10.40	16.06	2.23	0.0499
Liquidity (2)								
Liquid assets proportion (LIQ_ASST)	45	24.62	3.39	10	22.48	3.51	1.75	0.1031
Loans to deposits (LNS_DEP)	45	68.32	23.25	10	70.13	18.30	-0.27	0.7918

Source: FSA and PRA regulatory returns and author's calculation. Grey shading highlights differences at the 10% level of better.

Table 5D
Mean Comparison Tests
(at 200912)

	Less Intensive Responses			More Intensive Responses			Mean t-test	
CAMEL Proxy (Number of Variables)	Observations	Mean	Standard Deviation	Observations	Mean	Standard Deviation	t	Probability
Capital Adequacy (3)								
Tier 1 Leverage Ratio (T1LEV)	46	5.94	1.76	5	4.64	1.21	2.17	0.0729
Tier 1 Risk-Based Ratio (T1RBC)	46	15.15	4.72	5	13.08	3.78	1.30	0.3042
Total Risk-Based Ratio (TOTRBC)	46	16.86	4.65	5	15.85	1.84	0.95	0.3628
Asset Quality (9)								
1st Mortgage Arrears % (ARFSRP_I)	46	2.15	3.47	5	1.83	1.21	0.43	0.6772
Other Mortgage Arrears % (ARFSRP_O)	36	5.97	19.25	4	3.37	5.96	0.59	0.5633
Other Arrears on Loans to Individuals % (AROTHR_I)	9	12.02	13.19	2	7.73	10.93	0.48	0.6829
Other Arrears on Other Loans % (AROTHR_O)	34	0.27	0.89	4	0.03	0.05	1.54	0.1316
Repossessed loans to total assets (REPOSSES)	46	0.04	0.22	5	0.19	0.41	-0.82	0.4535
Provision coverage % (PROV_ARRS)	46	21.84	33.98	5	6.95	14.46	1.82	0.0990
Provisions to total loans (PROV_LNS)	46	0.24	0.22	5	0.10	0.20	1.44	0.2095
Total loans to assets (LNS_ASST)	46	73.46	4.58	5	73.92	1.67	-0.46	0.6556
Risk-weighted assets to total assets (RWA_ASST)	46	39.57	6.65	5	35.87	6.25	1.25	0.2656
Management (5)								
Efficiency (cost to income) ratio (EFF_NCY)	46	68.79	17.45	5	106.79	47.22	-1.79	0.1465
Residential real estate concentration (RESRE_TA)	46	66.79	8.78	5	67.73	5.97	-0.32	0.7611
Other secured loans (OTH_FSOL)	46	1.23	3.20	5	1.72	3.10	-0.33	0.7534
Real estate development loans (DEVEL_TA)	46	4.68	6.50	5	4.83	5.75	-0.06	0.9572
Asset Size (log of total assets)	46	13.29	1.76	5	14.96	1.58	0.10	0.9189
Earnings Performance (2)								
Return on Average Assets (ROA)	46	0.31	0.26	5	-0.03	0.35	2.15	0.0910
Return on Average Equity (ROE)	46	4.16	3.29	5	-1.23	4.38	2.67	0.0492
Liquidity (2)								
Liquid assets proportion (LIQ_ASST)	46	25.06	4.72	5	23.93	1.30	1.25	0.2258
Loans to deposits (LNS_DEP)	46	71.19	14.76	5	50.68	24.67	1.82	0.1370

Source: FSA and PRA regulatory returns and author's calculation. Grey shading highlights differences at the 10% level of better.

Table 6a
Analysis of Response Intensity
Single-Period Logistic Models

Variable	Expected Sign[a]	Model 1a (200512)	Model 2a (2000612)	Model 3a (200712)	Model 4a (200812)	Model 5a (200912)
Constant		4.3478**	4.2476**	3.14392	5.6661***	1.1555
Tier 1 Leverage Ratio	-	-0.9983**	-1.001**	-0.8325**	-1.5915***	-0.6482*
Observations		58	58	46	55	51
Log likelihood		-24.0209	-24.3464	-18.632	-16.9046	-14.2745
Wald Chi-Square		5.68***	5.45***	3.61**	9.52***	3.17*
Pseudo R^2		0.1876	0.1766	0.1232	0.3518	0.1004

Table 6b
Analysis of Response Intensity
Single-Period Logistic Models

Variable	Expected Sign[a]	Model 1b (200512)	Model 2b (2000612)	Model 3b (200712)	Model 4b (200812)	Model 5b (200912)
Constant		0.7880	0.1273	2.1010	9.8225***	3.9298
Tier 1 Leverage Ratio	-	-1.4266	-1.2426	-2.1745*	-2.3852***	-1.2190
Tier 1 Risk-Based Capital Ratio	-	-0.0905	-0.2391	0.4781	0.3410	0.3516
Total Risk-Based Capital Ratio	-	0.5086	0.6047	0.2091	-0.3220	-0.2924
Observations		58	58	46	55	51
Log likelihood		-22.7228	-22.2989	-17.8638	-15.8464	-14.3166
Wald Chi-Square		10.23**	11.09**	6.13*	9.40**	3.28
Pseudo R^2		0.2315	0.2459	0.1595	0.3923	0.1248

[a] Expected sign shows the expected effect of an increase in the variable on the likelihood of a more intensive response.
*** (**) {*} Indicates significance at the 0.01 (0.05) {0.10} level.

Table 7

Analysis of Response Intensity Using Expanded Single-Period Logistic Models

This table reports five separate single-period logistic models based on data from each of the year-ends 2005, 2006, 2007, 2008 and 2009 to explain the type of responses that occurred in the window of time spanning from the financial data date to the end of 2011.

Variable	Expected Sign[a]	Model 1c (200512)	Model 2c (2000612)	Model 3c (200712)	Model 4c (200812)	Model 5c (200912)
Constant		142.5865**	68.2166	28.7468	-1.1680	22.8270
Tier 1 Leverage Ratio	-	-1.2248*	-1.1371**	-0.8392*	-2.6909**	-1.5774**
Arrears rate on secured mortgages	+	0. 6609	0.8401	0.3731	-0.0322	-1.4573**
Ratio of loans to assets	+	-1.3771**	-0.5751	-0.2389	0.0489	-0.2499
Efficiency Ratio	+	0.0128	-0.0391	-0.0098	0.0496	0.0713*
Return on Assets	-	-8.4899***	-12.6549	-8.8687	-2.0730**	-8.0528***
Liquid Assets to Total Assets	-/+	-1.3715**	-0.5918	-0.1779	0.1709	-0.0667
Log likelihood		-18.5551	-19.5669	-15.4990	-10.5816	-6.4862
Wald Chi-Square		12.13*	11.87**	10.77*	9.78*	17.81**
Pseudo R^2		0.3725	0.3383	0.2708	0.5910	0.6035
Number of observations		58	58	46	54	51
Number and % of Significant Variables						
At 1% level		1 (17%)	0	0	0	1 (20%)
At 5% level		2 (33%)	1 (17%)	0	2 (33%)	2 (40%)
At 10% level		1 (17%)	0	1 (17%)	0	1 (20%)
Total		4 (67%)	1 (17%)	1 (17%)	2 (33%)	4 (80%)

[a] Expected sign shows the expected effect of an increase in the variable on the likelihood of a more intensive response

*** (**) {*} Indicates significance at the 0.01 (0.05) {0.10} level.

Table 8

Analysis of Response Intensity Using Multi-Period (Pooled) Logistic Models

This table shows multi-period logistic model results estimated using quarterly financial data spanning year-end 2005 to year-end 2010 to explain response intensity that occurred during the six-year period spanning the financial crisis, 2006 to 2011. Models 6, 7 and 8 include only the Tier 1 leverage ratio, Tier 1 and Total Risk-Based Capital Ratios, respectively. Model 9 includes all three capital measures. Models 10, 11 and 12 expand Models 6, 7, and 8, respectively, and control for all CAMEL attributes by incorporating a measure of arrears rate on secured mortgages, the ratio of loans to assets, management efficiency, return on average assets and liquid assets. The chi-square statistic for the test of the joint hypothesis that the omitted variables from the constrained model (Model 6) compared with the unconstrained model (Model 9) is 0.051. With 5 degrees of freedom, the probability of observing this value or a smaller value is less than 5 percent, suggesting that the additional risk-based ratios add no explanatory power. Model 10 employed a stepwise selection process which evaluates the significance of each variable in a specification that includes all candidate variables and then progressively eliminates those variables that are not statistically significant at the 10 percent level.

Variable	Expected Sign[a]	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Constant		-0.2929277	-1.08379**	-.2748543	-.4470604	-32.68645***	-12.54417	-1.63127
Tier 1 Leverage Ratio	-	-0.9120383***			-.8483364***	-1.698328***		
Tier 1 Risk-based Ratio	-		-.3075115***		-.041133		-.3644381**	
Total Risk-based Ratio	-			-.3066748**	.0229653			-.2469945**
Arrears rate on secured mortgages	+					.4413764***	.2087565**	.1390281**
Loans to Assets	+					.3816574***	.1380818*	.0294960
Efficiency Ratio	+					.0058014***	.0051408***	.0041616***
Return on Assets	-					-1.986111***	-1.878409***	-1.758282***
Liquid Assets to Total Assets	+/-					.2322573*	.0285474	-.1111968
Observations		1242	1242	1242	1241	1230	1230	1230
Wald Chi Square		18.31***	35.00***	5.95**	20.49***	121.00***	164.26***	189.55***
Pseudo-R2		0.2072	0.1494	0.0612	0.2076	0.5082	0.4242	0.3533
Log likelihood		-49.8940	-53.5406	-59.0885	-49.8685	-28.5624	-33.4438	-37.5593

[a] Expected sign shows the expected effect of an increase in the variable on the likelihood of a more intensive response.
*** (**) {*} Indicates significance at the 0.01 (0.05) {0.10} level.

Table 9
Analysis of Responsive Intensity Using Multi-Period (Random Effects) Logistic Models

This table shows multi-period logistic model results estimated using random effects that allows for individual building society heterogeneity. Models employ quarterly financial data spanning year-end 2005 to year-end 2010 to explain response intensity that occurred during the six-year period spanning the financial crisis, 2006 to 2011. These models exploit the heterogeneity in the baseline models reported in Table 8. The estimate of the random error in all models is not significant, implying that building societies are relatively homogeneous in terms of the baseline response probability after accounting for the CAMEL attributes. These results provide further evidence of robustness of the baseline model estimated using a standard, pooled logistic approach.

Variable	Expected Sign	Model 6a	Model 7a	Model 8a	Model 10a	Model 11a	Model 12a
Constant		-.2710661	-1.083843	-.2743076	-32.67864*	-13.75134	-1.63108
Tier 1 Leverage Ratio	-	-.9230909***			-1.698014***		
Tier 1 Risk-based Ratio	-		-.307467***			-.3912739**	
Total Risk-based Ratio	-			-.3066912***			-.246991
Arrears rate on secured mortgages	+				.4412946**	.2247349*	.1390189
Loans to Assets	+				.3815588*	.1521622	.0294993
Efficiency Ratio	+				.0058003***	.0054001**	.0041614**
Return on Assets	-				-1.985828***	-1.975239***	-1.75807***
Liquid Assets to Total Assets	+/-				.2322203	.0382056	-.1111999
Random Error		-2.60006	-12.45742	-12.71647	-10.49509	-10.02812	-10.97935
Observations		1241	1242	1242	1230	1230	1230
Wald Chi Square		9.27***	18.86***	6.67***	27.47***	5.44**	29.32***
Pseudo-R2		0.1913	0.1334	0.0452	0.4049	0.3215	0.2500
Log likelihood		-49.892693	-53.540683	-59.08857	-28.562447	-33.405463	-37.55935

*** (**) {*} Indicates significance at the 0.01 (0.05) {0.10} level. Random error reflects log of variance.

Table 10

Analysis of Response Intensity Using Multi-period (Pooled) Logistic Models with Lagged Explanatory Variables

This table shows multi-period panel model results estimated using quarterly financial data spanning year-end 2005 to year-end 2010 to explain incidents of more responsive responses that occurred during the six-year period spanning the financial crisis, 2006 to 2011. Models differ according to the distance of the lagged explanatory variables included. For example, the 4-quarter ahead model (or one-year risk profile model) uses financial attributes measured four quarters prior to a more intensive response, while the 8-quarter ahead model (or two-year risk profile model) uses financial attributes measured eight quarters prior to response. The model with no lags is Model 10 as reported in Table 8.

Variable	Expected Sign[a]	No Lag	1 Quarter Lag	2 Quarter Lag	3 Quarter Lag	4 Quarter Lag	8 Quarter Lag
Constant		-32.68645***	-39.01854	.4197251	-.2022058	-4.16611	-19.62177
Tier 1 Leverage Ratio	-	-1.698328***	-1.196771***	-1.127916***	-.8842882**	-.5806246**	-.8315727**
Arrears rate on secured mortgages	+	.4413764***	.2643656**	-.0014081	.0169025	-.233980	-.1834808
Loans to Assets	+	.3816574***	.3899936	-.0147652	-.0017313	.0075395	.2032222
Efficiency Ratio	+	.0058014***	.0256403***	.0219095	-.000897	.0178687	.0094983
Return on Assets	-	-1.986111***	-.6260978	-.5104915	-1.394318***	-.756222**	-.6407476*
Liquid Assets to Total Assets	+/-	.2322573*	.3608707	-.0038608	.0192105	.049245	.1774261
Observations		1230	1175	1119	1064	1230	784
Wald Chi Square		121.00***	54.12***	69.15***	13.93**	14.75**	14.78**
Pseudo-R2		0.5082	0.2958	0.2023	0.1710	0.0836	0.0931
Log likelihood		-28.5624	-37.1923	-41.7744	-46.9434	-47.1175	-52.4697

[a] Expected sign shows the expected effect of an increase in the variable on the likelihood of a more intensive response.

*** (**) {*} Indicates significance at the 0.01 (0.05) {0.10} level.

Table 11

Analysis of Response Intensity Using Multi-period (Pooled) Logistic Models with Lagged Explanatory Variables

This table shows multi-period panel model results estimated using quarterly financial data spanning year-end 2005 to year-end 2010 to explain incidents of more intensive responses that occurred during the six-year period spanning the financial crisis, 2006 to 2011. Each model employs a stepwise selection process in identifying significant variables and differs according to the distance of the lagged explanatory variables included. For example, the 4-quarter ahead model (or one-year risk profile model) uses financial attributes measured four quarters prior to response, while the 8-quarter ahead model (or two-year risk profile model) uses financial attributes measured eight quarters prior to response. The model with no lags is Model 10 as reported in Table 8.

Variable	**No Lag**	**1 Quarter Lag**	**2 Quarter Lag**	**3 Quarter Lag**	**4 Quarter Lag**	**8 Quarter Lag**
Constant	-32.68645***	.1751913	-.2957065	1.890663	-1.173069	-.7918476
Tier 1 Leverage Ratio	-1.698328***	-1.322369***	-1.418996***	-.8723817***	-.664382 **	-.6599005 **
Arrears rate on secured mortgages	.4413764***	.3178515**	-.0014081			
Loans to Assets	.0058014***					
Provisions to loans			1.362828***			
Ratio of repossessed propertios to assets				-3.125294**		
Provision coverage of arrears				.0013178**		
Efficiency Ratio	.0058014***	.0095961***	.0250806***			
Return on Assets	-1.986111***	-1.678523***		-2.55038***	-.9367055***	-.71015***
Liquid Assets to Total Assets	.2322573*					
LNS_DEP				-.029184**		
Observations	1230	1093	1038	984	929	713
Wald Chi Square	121.00***	24.80***	52.66***	35.06	12.68**	10.94***
Pseudo-R2	0.5082	0.3714	0.2562	0.3361	0.0860	0.0749
Log likelihood	-28.5624	-32.7853	-34.8820	-30.8467	-37.6487	-40.5895

*** (**) {*} Indicates significance at the 0.01 (0.05) {0.10} level.