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Predicting bank financial distress prior to crises

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Abstract

Credit-rating agencies (CRAs) do not always provide timely advice on credit downgrades. CRAs have also been criticised for providing overly optimistic ratings for financial institutions prior to financial crises. Nevertheless, timely and accurate credit ratings are particularly significant when financial institutions are scrutinised because the latter occupy a central role in economic activity. This study illustrates how the non-parametric technique Data Envelopment Analysis (DEA) can be used as a forward-looking alternative method to flag bank holding companies likely to become distressed in the near future. Various financial performance models are tested. The results obtained generally support DEA's discriminatory and predictive power, suggesting that DEA can identify distressed banks up to two years in advance. Robustness tests reveal that DEA has a stable efficient frontier and that the technique's discriminatory and predictive powers prevail even after data perturbations. DEA can be used as a preliminary off-site screening tool by regulators; used by business managers to gauge the likelihood of financial distress in the near future and their current standing among competitors; and applied by investors to evaluate the risk in a bank share investment. In conclusion, DEA may be useful in assisting regulatory agencies, managers and investors alike in making economic decisions.

1. Introduction

The recent Global Financial Crisis (GFC) of 2007-2008 originated in the U.S. subprime residential mortgage market. At a time of low official interest rates, financial institutions and investors sought investment opportunities that offered higher yields. However, in an environment of increasing house prices and investment-grade ratings backed by third-parties, the market did not fully assess or review the potential default risks. To make matters worse, the first downgrading actions taken by Moody's and Standard and Poor's were as late as in November 2006 and February 2007, respectively (Crouhy et al., 2008), casting doubt on the reliability of credit ratings. The severity of this crisis has been particularly evident in the banking sector due to investment banking activities and large off-balance sheet transactions, and contagion.

Given the well-documented impact of the GFC on the global banking sector and its burden on the central governments, it is compelling to find a technique or methodology to distinguish between healthy and distressed institutions and predict financial distress. While credit ratings have historically been one of the most commonly used indicators of financial distress, the GFC has highlighted their inadequacies in terms of timeliness, quality, and conflict of interest. Other distress or bankruptcy predictive tools found in literature have shortcomings such as the requirement of a representative sample to estimate model parameters, limited scope for decision making (e.g., accounting ratios), and normality assumptions that may not hold.

The empirical analysis technique used in this paper, Data Envelopment Analysis (DEA), is an intuitive non-parametric technique that accounts for interaction among multiple input and output variables. In other words, DEA enables multi-dimensional decision making, and can also highlight efficiency improvement opportunities for organizations. This paper illustrates how DEA can be used as a forward-looking alternative method to predict financial distress that may complement credit ratings on bank holding companies (BHCs) or replace credit ratings when they are unavailable to the public. Towards this objective the paper explores whether an *ex-post* sample of financially distressed BHCs can be identified as inefficient by DEA using pre-GFC financial data.

The main thrust of this paper is to predict financial distress in U.S. bank holding companies in the context of the recent GFC. We also want to investigate how far in advance DEA modelling can correctly predict the financial distress incurred during the GFC. To achieve this goal, the financial performance efficiency is empirically measured using DEA, where the relative efficiency of each unit within the sample can be computed by defining inputs and outputs that capture bank production. We consider DEA particularly fit for the task on hand because the technique is highly forgiving of correlated variables most parametric techniques would not tolerate, where the selection of such variables is driven by production theory, expert opinion, or a combination. That is, DEA is not stymied by distributional considerations that limit parametric techniques.

This study contributes to extant literature in a number of ways. For example, the paper makes a methodological contribution by showing how DEA can be used as a forward-looking method to flag financial institutions likely to become distressed in the near future. In addition, while prior literature demonstrates DEA's predictive power (see Pille and Paradi, 2002, Paradi et al., 2004, Premachandra et al., 2009, and Avkiran and Morita, 2010), there is still some ambiguity over how to select financial variables for DEA modelling and robustness of results. This paper addresses such potential problems in an effort to encourage new applications of DEA in banking.

The study also highlights regulatory implications and insights for bank managers. Financial institutions, acting as financial intermediaries, are critical players in the economy and the public have vested interests in their performance (Ayadi et al., 1998). Consequently, they often operate in a highly regulated environment and receive a great deal of regulatory attention. Furthermore, Clare and Priestley (2002) argue that bank failures can be contagious, leading to other failures, which in turn could have a major adverse impact on the real economy. Thus, a study of financial distress can assist government regulators in supervising banks in a more effective manner by flagging those likely to be financially distressed in the near future. In many countries, a variety of early warning systems (EWSs) have been used for years to monitor the risk of banks. However, the repeated occurrence of banking crises during the past twenty years delivers an important message: safeguarding the banking system is not easy (Demyanyk and Hasan, 2010). Studies of default risks of financial institutions should provide insights for economic decision makers such as regulators, bank managers and investors by flagging distressed banks from an *ex-ante* standpoint.

The rest of this paper is structured as follows. Section 2 presents a literature review. Section 3 introduces the conceptual framework. The data and research method are described in Section 4. Section 5 contains the main results and inferences. Robustness is examined in section 6. Section 7 offers concluding remarks.

2. Literature review

2.1 *Predicting bank financial distress*

The use of DEA to predict credit risk and, therefore, financial distress in financial institutions has not been attempted in prior literature. However, researchers have been addressing the prediction of financial distress, default probabilities and failure in banks by applying various other methodologies. For example, Abrams and Huang (1987) adopted a probit model incorporating various bank structure variables to predict bank failures and concluded that banks' likelihoods of default had been reflected in the accounting data in their balance sheet and income statements. Wheelock and Wilson (2000) used a competing-risk model to identify the characteristics resulting in U.S. banks' failure or acquisition. Kolari et al. (2002) suggested that computer-based Early Warning Systems (EWSs) can predict large U.S. bank failures. Canbas et al. (2005) predicted Turkish commercial banks' failure via multivariate statistical analysis of financial structures. They combined four parametric models to construct an Integrated Early Warning System (IEWS), which was reported to have high predictive ability for differentiation between sound and troubled banks. Camara et al. (2011) introduced a modification of Merton's (1976) model to estimate default probabilities from stock and option market prices by assuming that the stock price followed a delta-geometric random walk.

In addition, a large number of publications on banking systems demonstrate DEA's appeal as a benchmarking tool, but none of them have attempted to use DEA to predict financial distress. For example, Barr et al. (1993) derived a model to quantify the management efficiency of 930 banks using DEA. Sathye (2001) studied the technical efficiency or X-efficiency of 29 Australian banks in 1996 by applying a DEA model and compared the results with European and American banks. Casu and Molyneux (2003) employed DEA to estimate the productive efficiency of 530 European banks from 1993 to 1997 (after the creation of the Single Internal Market). Chiu et al. (2010) used DEA to measure the operating efficiency of the Taiwanese banking system by using credit ratings as an output.

Among those papers applying DEA, some researchers have used DEA as a predictive tool, but with foci other than financial distress. For example, Pille and Paradi (2002) developed DEA models along with the modified Z-score model and equity-to-asset ratio to detect failure in credit unions in Ontario, Canada, from 1991 to 1996. However, the authors' main focus was on the needs of the government regulators; and, they tested which DEA models were equally competent in predicting bankruptcy. Pille and Paradi (2002) presented a pool of input and output candidates, from which they appear to arbitrarily select two variables as inputs and three to four variables as outputs. Thus, there is no way of telling whether their DEA model was randomly predictive or whether the satisfactory results were obtained through trial and error.

Paradi et al. (2004) also used DEA and introduced the worst-practice DEA, which is conceptually the reverse of traditional DEA, to evaluate credit risk and bankruptcy in the manufacturing sector. In bankruptcy predictions using best-practice DEA, the intention is to identify the best financial performers by selecting output variables where higher levels add to financial health and input variables that detract from financial distress. That is, in best-practice DEA modelling, the best performers can be identified using desirable variables such as earnings and capital as outputs, and undesirable variables such as costs as inputs. In worst-practice DEA modelling, usually these roles are reversed where undesirable variables that contribute to financial distress or failures are used as outputs, while desirable variables are used as inputs. Thus, poor financial performers can be identified against a frontier constructed on worst performance, giving rise to the name 'worst-practice DEA'.

Apart from using the worst-practice DEA model, Paradi et al. (2004) used 1996 data as an evaluation sample and 1997 data as a validation sample. Their initial pool of variables for input and output candidates was based on literature. From a pool of ten variables, they tried different combinations of inputs and outputs. The authors show that one of those combinations provides the most correct prediction in the estimation sample. They then apply the same set of inputs and outputs to a validation sample. The results are convincing: when the best-practice DEA model is combined with the worst-practice DEA model, the bankruptcy prediction is 100% after layer 3, i.e. after removal of banks on three consecutive efficient frontiers.

There are a number of differences between Paradi et al. (2004) and this paper. Firstly, they seek to predict corporate failure one year in advance, while the objective of this paper is to explore how far in advance pre-GFC data can be used by DEA to predict financial distress in banks in the period leading up to the GFC. Secondly, Paradi et al. (2004) use radial output-oriented DEA for their worst-practice model and radial input-oriented DEA for their best-practice model. The current paper adopts the DEA model of slacks-based measure of super-efficiency by Tone (2002) where inefficiencies (known as 'slacks' in DEA jargon) in all the variables are accounted for in computing an overall performance score. Thirdly, the core research design in this paper does not use a validation sample, but a number of independent tests are executed to test robustness of results.

Another paper of interest is Premachandra et al. (2009) who compare DEA to logistic regression in terms of corporate bankruptcy prediction. According to Premachandra et al. (2009), when applying logistic regression, the parameters of the model can be estimated from an *ex-post* sample that includes failed and non-failed firms. Through extrapolation from this sample, corporate failure can be predicted *ex-ante*. However, there are also some differences between their study and this paper. Firstly, their focus was on bankruptcy, which is the most extreme outcome of financial distress. Indeed, financial distress does not necessarily lead to default or bankruptcy. This is also why DEA is particularly attractive, as it can offer potential improvement guidelines for managers and regulators before experiencing bankruptcy.

Secondly, Premachandra et al. (2009) compare the predictive ability of DEA with logistic regression, while the focus in this paper is on using DEA to complement credit ratings, or substitute for ratings when they are not available. Thirdly, the authors only include firms matched to the bankrupt firms in the sample, while in the current paper, all bank holding companies with available data are included. Lastly, in Premachandra et al. (2009) results are based on small sample sizes – a situation that violates the generally accepted practices on dimensionality in DEA literature.

Finally, a recent study conducted by Avkiran and Morita (2010) iteratively identifies various combinations of financial ratios and then apply DEA to predict Japanese bank stock performance. The authors have a different focus to that of the current study where their intention was to inform readers about which financial ratios to monitor in forecasting stock performance over a number of years.

In summary, to the best of our knowledge, application of DEA to predict financial distress prior to crises has not been attempted. Moreover, an issue with some of the above studies that use DEA as predictive tools is the inadequate attention given to justify the choice of variables and to convince readers that DEA results can withstand robustness tests. This paper proposes various financial performance models to guide users in bringing together performance variables, as well as test for robustness of DEA results.

2.2 The role of credit-rating agencies and their shortcomings

Traditional wisdom argues that credit-rating agencies (CRAs) play a fundamental role in international financial markets by increasing market efficiency and reducing costs for borrowers. The issuance of credit ratings can impact decision making by various parties including investors, regulators and bankers. For example, under Basel II, capital adequacy framework allows banks to rely on external ratings assigned by recognised CRAs when calculating capital charges (see discussion in Pasiouras et al., 2007). Therefore, under Basel II, the timely issuance of reliable credit ratings has been important in facilitating bank financial transactions. However, the Basel III accord under development since the GFC is attempting to mitigate reliance on external credit ratings - instead expecting banks to undertake internal evaluation of exposures related to securitisation (BIS, 2011, p.4). Nevertheless, we do not expect the global role of CRAs to diminish in any substantial way in the near future.

Nevertheless, it has been argued that CRAs do not always provide timely downgrade advice on companies. There have been debates concerning whether these CRAs have given effective predictions during financial crises and whether, to some extent, their ratings may have added to the severity of crises. For example, Radelet et al. (1998) argue that the tardy downgrading by the CRAs led to their failure to predict the 1997 Asian financial crisis and, therefore, caused further withdrawals by creditors. Likewise, during the 2007-2008 global financial crisis, rating agencies have also been criticised for providing overly optimistic ratings for financial institutions. Crouhy et al. (2008) argue that the main lesson learned from this crisis is the need for timely issuance of accurate credit ratings.

Moreover, Hill and Faff (2010) claim that, apart from the criticism of rating agencies' belated downgrading of bank ratings, the quality of their ratings is also questionable based on their failure to comprehensively assess the risk of collateralised debt obligations (CDOs). For example, the risks of complex structured products, such as CDOs, were not viewed by investors as excessive due to the investment grade credit ratings (usually AAA). This evidence is consistent with the claim by the Association for Financial Professionals (AFP) (2008, p.1) that "1) the information provided by CRAs is not always timely or accurate and 2) the CRAs are primarily serving the interest of parties other than investors".

Overall, inadequacy of credit ratings during the GFC can be traced to problems with timeliness, quality and conflict of interest. Ashcraft et al. (2010) argue that, before the GFC, their early default indicators, namely, appreciation of home prices and underwriting summary statistics, suggested the increase of mortgage credit risk, yet the CRAs did not react until after mid-2007. Altman and Rijken (2004) compare the ratings issued by CRAs to their ratio-based prediction model and find that the agencies tend to focus on the long-term rather than a one-year investment horizon. They explain the motivation behind this long-term perspective as achieving rating stability by referring to Standard & Poor's rating criteria document. From the investors' viewpoint, this long-term focus can be interpreted as ensuring lower costs for portfolio rebalancing; however, this information can misguide investment decisions if the true status of a firm cannot be reflected in a timely manner.

Another indication of why credit ratings may not be timely enough to predict financial distress is that CRAs only adjust their ratings when they believe that the obligor's likelihood of payment has fundamentally changed (Galil, 2003). Yet, if the ratings are capable of indicating default or distress, when a debt instrument gets closer to maturity, its rating should change to reflect a lower probability of default. Moreover, the AFP (2002) survey reveals that only 37% of corporate practitioners believe the changes in credit ratings are timely for their investment decision-making.

Galil (2003) use the proportional hazard model to parameterise credit ratings. The results demonstrate inadequate incorporation of publicly available information in credit ratings. Galil shows that, even when controlling for the informational content of ratings, factors such as size, leverage and industrial classification can still explain default probability. For example, in 2001, the CRAs continued to rate the debt of Enron as 'investment-grade' days before its bankruptcy. Consequently, the US Congress joined the debate about ratings quality in ways such as the introduction of the Sarbanes-Oxley Act of 2002, which requires SEC to study the role and function of CRAs (AFP, 2002). A more recent example is the introduction of the Dodd-Frank Wall Street Reform and the Consumer Protection Act in 2010, where section 931 of the Act states that "In the recent financial crisis, the ratings on structured financial products have proven to be inaccurate. This inaccuracy contributed significantly to the mismanagement of risks by financial institutions and investors…" (Congress of the USA, 2010, p.497).

Most debt issuers (95%) request ratings from CRAs and pay fees based on the size of the issue, which introduces concerns about conflict of interest (Galil, 2003). Indeed, the Dodd-Frank Wall Street Reform and the Consumer Protection Act also recognise the conflict of interest faced by CRAs and highlights the need for careful monitoring. A number of researchers have been aware of this issue and have conducted studies to address such concerns. For instance, models built by Bolton et al. (forthcoming) have found that when an issuer is more important to a CRA and the investors in general are more trusting of ratings, the CRA is more inclined to issue favourable ratings. Such results are consistent with the findings in the AFP (2002) survey, which discloses that only 22% of corporate practitioners agree that the rating agencies act in the best interest of the investors.

Inadequacies of credit ratings discussed above highlight the need for a forward-looking technique. Losses associated with financial distress can be minimised to the extent that an alternative technique can predict distress well in advance. AFP's survey (2002) reveals that, apart from looking at credit ratings, 83% of corporate practitioners turn to alternative sources of information to make investment decisions, such as Dun & Bradstreet (48%), investment banker research (36%), and A.M. Best Company (26%). More significantly, the survey indicates that 42% of practitioners rely on proprietary research. The latter suggests that practitioners may be conducive to undertaking in-house research using DEA.

Given that financial institutions occupy a central role in economic activity and that their credit ratings can be questionable, this study aims to develop application of DEA as a forward-looking alternative method to predict financial distress. The study, thus, can complement credit ratings of financial institutions or fill the gap when credit ratings are not available.

2.3 DEA as a predictive method

Before proceeding, we would like to re-iterate the main reasons for using DEA as a forward-looking method to predict financial distress. There are three primary supporting arguments from an *ex-ante* standpoint.

The current study is inspired by a number of prior studies. Although the traditional DEA technique was originally not intended for predictive purposes when first proposed in 1978, Pille and Paradi (2002), Paradi et al. (2004), Premachandra et al. (2009), and Avkiran and Morita (2010) have all successfully developed predictive models using the DEA technique. Given the feasibility of using DEA to develop predictive models, this paper also uses DEA, albeit to identify banks in financial distress given the drawbacks of credit ratings or their absence. Moreover, this paper identifies the inputs and outputs from prior literature that focus on capturing financial distress, i.e., those variables associated with credit quality that change the most for problem financial institutions.

Because DEA generates efficiency scores or estimates, it is essential to construct a linkage between 'financial efficiency or performance' and 'financial distress'. However, it should be noted that the efficiency scores would vary by study foci that drive the choices of inputs and outputs. In a traditional DEA application, which uses production inputs such as number of employees and total assets, and outputs such as non-interest revenues and total loans, the obtained score can reflect an organisation's *operating efficiency* in terms of input minimisation, output maximisation or both. However, because this paper includes only inputs and outputs associated with financial distress, the relative efficiency scores thus generated represent *financial performance*. That is, our application of DEA should indicate how efficient a financial institution is in minimising variables that indicate increasing financial distress and maximising variables that indicate increasing financial health. The selection of such variables is detailed in the following section.

3. Conceptual framework

3.1 Distress criteria

This paper uses an *ex-post* sample of distressed and non-distressed BHCs to test DEA's power to predict financial distress. By using only annual financial data that were available before the GFC (from 2004 to 2006), DEA is used to flag those BHCs that are found to be distressed during and after the GFC (2007 to 2009).

Below, we outline the financial distress criteria used to separate the initial sample of BHCs into 'distressed' and 'non-distressed' groups based on their 2007-2009 performance. Prior literature suggests the following criteria to determine distress:

1. *Failure by the end of 2009*

   As indicated earlier, failure or bankruptcy is the most extreme outcome of financial distress. The Federal Deposit Insurance Corporation (FDIC) is often appointed as the receiver for failed banks and the list of failed banks is available from the FDIC website. In addition, both BHCs filing for Chapter 11 bankruptcy and those appearing on BankruptcyData.com were checked.

   In addition, BHCs with a status indicated in the BankScope database as (1) bankrupt, (2) dissolved, or (3) in liquidation were considered failed (the last criterion was also adopted by Mannasoo and Mayes, 2009).

2. *Recipient of substantial federal government bailout funds*

   The recent GFC has enabled a list of distressed banks to be identified by their successful application for Troubled Assets Relief Program (TARP). The applications from distressed banks for bailout funds were reviewed internally by the U.S. Treasury with the assistance of regulatory bodies. Although the bailout decision made by the Treasury may sometimes be politically motivated, this criterion was adopted by Buehler et al. (2009), where distressed firms are identified as having received 'substantial' government bailouts. The authors defined 'substantial' as total bailout greater than 30% of Tier 1 capital at the financial year end. In this paper, Tier 1 capital at the 2007 financial year-end for all bailout fund recipient BHCs was downloaded from BankScope. Following Buehler et al. (2009), the 30% cut-off criterion is used.

3. *Keyword search combining BHC and 'rescue', 'bailout', 'distressed merger', 'financial support', etc.*

   This last criterion serves to ensure that all distressed BHCs have been captured. This criterion is consistent with Cihak and Poghosyan (2009), who used a keyword search to capture references to failing banks. Their source of information is NewsPlus/Factiva. In this paper, Bloomberg, Reuters, and BHC official websites are the main sources for the keyword search.

In summary, after applying the first two distress criteria, 48 BHCs were classified as 'distressed' and 138 BHCs were classified as 'non-distressed'. From the 'distressed' group, 25 (52%) satisfy the first criterion ('failed') and 23 (48%) satisfy the second criterion ('bailout'). No additional 'distressed' bank was found by applying the third criterion.

3.2 Financial performance models

After identifying the distressed and non-distressed groups, the next step is to identify potential input and output variables suitable for predictive DEA modelling. DEA is a non-parametric, multi-dimensional method used to measure relative efficiency that processes the simultaneous interaction of various inputs and outputs. To rank and compare the two groups of firms according to their efficiency scores, the inputs and outputs in this study's DEA modelling use *volume* measures that either reduce financial distress (i.e., outputs) or raise financial distress (i.e., inputs). We note that normalisation, say, by dividing with total assets, is unnecessary in DEA because of its non-parametric nature and its ability to account for returns-to-scale.

Literature suggests a number of factors that are thought to be associated with distress or probability of default. In the corporate finance literature, predicting failure using firm-specific characteristics together with financial structures of firms is attributed to Altman (1968, 1977), who employed multivariate discriminant analysis based on financial ratios to propose the well-known Z-score. Following the work of Altman, a series of publications sought to use variables that are able to discriminate failed firms from financially healthy firms. In the rest of the paper, only those variables applicable to financial institutions are selected.

3.2.1 CAMELS model

Initially, the CAMELS rating is used to categorise relevant financial variables encountered in literature. CAMELS stands for *capital* adequacy (C), *asset* quality (A), *management* efficiency (M), *earnings* (E), *liquidity* (L) and *sensitivity* to market risk (S). Variables in each of these categories are popular with regulators and supervisory agencies in monitoring bank risks, developing early warning systems, and ensuring the safety and soundness of a banking system (Cole and Gunther, 1995; DeYoung, 1998; Curry et al., 2003; Oshinsky and Olin, 2006; Kumar and Ravi, 2007; Boyacioglu et al., 2009; Cihak and Poghosyan, 2009; Ravisankar and Ravi, 2010). However, because the variables used to determine CAMELS ratings are not publicly available (Jin et al., 2011), the following variables were selected under each CAMELS category after consideration of prior studies and the availability and consistency of data in BankScope and Compustat.

Capital adequacy (C)

Most studies use the ratio of total equity to total asset to measure capital adequacy. The motivations for not using the regulatory Tier 1 capital ratio (Tier 1 capital to risk-weighted assets) are consistent with Cihak and Poghosyan (2009): firstly, this information is not available across all BHCs across time, and secondly, the calculation of risk-weighted assets is arbitrary and open to manipulation.

Pille and Paradi (2002) argue that the ratio of total equity to total assets is a good predictor of failure. Canbas et al. (2005) suggest that an increase in the capital adequacy ratio has a positive impact on bank values. In other words, the greater the ratio, the greater is the financial strength of a bank and, therefore, the lower the default risk. Schaeck (2008) also agree that equity serves as a cushion between asset value and payments to debt holders.

In this paper, total equity is used to represent the ‘C’ category in the CAMELS model and an output in DEA.

Asset quality (A)

Loan quality is a statistically significant variable that has often been measured empirically by non-performing loans to total loans or to total assets, loan loss reserves to total assets and loan loss provisions to total loans. Because loans are the most risky assets for most financial institutions, the empirical findings on asset quality indicate that provision for loan losses differs significantly between problem and non-problem banks (Sinkey, 1975). Curry et al. (2003) posit that credit quality of loans, which can be measured by loan loss reserves to total assets and loan loss provisions to total assets, is associated with the likelihood of CAMELS ratings changes, reflecting financial distress. King et al. (2006) find that the ratio of loan loss reserves to total loans is higher for failed banks. This paper uses *loan loss reserves* as an input in DEA to account for asset quality because this measure is seen most often in extant literature.

Management efficiency (M)

The 'M' category has been empirically measured by non-interest expense to the sum of net interest income and non-interest income, personnel expenses to average assets, and cost to income ratio (Oshinsky and Olin, 2006; Boyacioglu et al., 2009; Poghosyan and Cihak, 2011). To measure management efficiency, DeYoung (1998) concludes that his results support the conventional belief that cost efficiency reflects management quality. The rationale here is that a well-managed bank is able to use resources more efficiently than poorly managed banks. DeYoung (1998) reveals the highest correlation of 0.402 between the ratio of non-interest costs to total revenues and the *M* rating in CAMELS. Thus, the current study will use the volume measure of *total non-interest expense* to account for management efficiency.

Earnings (E)

Earnings ratio, which is normally calculated by net income divided by total assets, is the most frequently used measure of profitability and should have a negative relationship with failure. Sinkey (1975) reviewed the empirical findings and stated that profitability is a good discriminator between problem and non-problem banks. Moreover, Abrams and Huang (1987) show that banks with lower earnings experiences exhibit higher probabilities of default at the 5% level of significance. In this paper, consistent with the consensus in prior literature (Martin, 1977; West, 1985; Wheelock and Wilson, 2000; Shumway, 2001; Canbas et al., 2005; Lanine and Vennet, 2006; Celik and Karatepe, 2007; Boyacioglu et al., 2009), *net income* is used as an output in DEA.

Liquidity (L)

Financial institutions with relatively illiquid assets are more likely to default. However, there are different measures of liquidity risk. Wheelock and Wilson (2000) measure liquidity with net purchases of federal funds scaled by total assets, whereas Canbas et al. (2005) consider the liquidity factor by applying the ratio of liquid assets divided by total assets. Alternatively, Distinguin et al. (2006) evaluate the liquidity category using the ratio of liquid assets to total deposits and borrowings. The current study adopts *liquid assets* as an output in DEA.

Size (S)

Size is considered here instead of 'sensitivity to market risk' because most studies ignore this CAMELS category, e.g., Wheelock and Wilson (2000), Oshinsky and Olin (2006), and Distinguin et al. (2006). Furthermore, the only study that takes into account sensitivity to market risk is Boyacioglu et al. (2009), in which trading securities to total assets, foreign assets to foreign liabilities, and net interest income to average asset are used. Due to either variable redundancy or unavailability, we were unable to consider those variables in our CAMELS model. Instead, size, which is proxied by total assets, is found to be negatively related to default risk in many studies including Abrams and Huang (1987), Wheelock and Wilson (2000), Kolari et al. (2002), Lanine and Vennet (2006), and Kato and Hagendorff (2010). This relationship can be attributable to the notion of 'too big to fail' and the diversification effect mentioned in Curry et al. (2003) and Kato and Hagendorff (2010). Thus, *total assets* is used as an output in DEA.

Summing up the key variables to emerge from CAMELS, inputs are loan loss reserves and total non-interest expense. Outputs consist of total equity, net income, liquid assets, and total assets.

3.2.2 Core profitability model (CPM)

Because there is no universal protocol for selecting input and output variables, in addition to using the CAMELS approach, the core profitability model (CPM) proposed by Avkiran (2011b) is considered as an alternative. CPM consists of the key performance indicators of total interest expense and non-interest expense as inputs, and gross interest and dividend income and total non-interest operating income as outputs. As its name suggests, CPM focuses on capturing how successful a bank is in maximising its profitability (Avkiran, 2011b). The rationale for using CPM to predict financial distress is that if a bank is efficient in maximising revenues while minimising costs, it is more likely to defend itself when exposed to a financial crisis and less likely to be bailed out by the government.

3.2.3 Market-based models

Flannery (1998) claims that market information can add value to bank distress prediction compared to the CAMELS indicators, which were based on historical accounting information. Curry et al. (2003) profess that not only academics but also U.S. bank regulators would like market signals to be incorporated into bank supervision. The foundation for this push is the belief in market efficiency or the rapid processing of publicly available information by financial markets. Similarly, Hillegeist et al. (2004) argue that the stock market provides an alternative and potentially superior source of information regarding financial distress because it does not rely solely on financial statements. Consequently, two market-based robustness tests are run where two variables in the CAMELS and CPM models are replaced with *annual stock return* and *market capitalisation*.

4. Data and research method

4.1 Data

The initial sample consists of 218 listed US bank holding companies (BHCs) extracted from BankScope. We focus on BHCs because most banks in the U.S., especially those banks at mature stages of operations, are owned by bank holding companies (Partnership for Progress, 2011). During the GFC, a large number of banks, including JP Morgan and Goldman Sachs, have become BHCs to take advantage of lower borrowing costs and emergency financial support. In addition, the structure of BHCs allows them to diversify their portfolio and banking activities, obtaining more stable sources of funding (Strafford, 2011). Partnership for Progress believes that for most banks, the question is when rather than whether to become a BHC. Another reason for focusing only on BHCs is DEA's homogeneity assumption. To allow meaningful peer benchmarking, all DMUs in a sample must share similar production processes. In other words, it is necessary to ensure that all the variables used in DEA models are relevant to the core operations of banks that comprise the sample.

To avoid look-ahead bias, the list of 218 BHCs is obtained from the 2004 BankScope disc provided by BankScope Bureau van Dijk Regional Client and IT Support. This 2004 disc only contains bank information that was available in and prior to 2004. Therefore, the 218 banks were already BHCs in 2004. To ensure consistency, we further eliminate 32 BHCs that were indicated as 'dissolved' in the 2005 and 2006 BankScope discs. Hence, the 186 banks that existed as BHCs consistently from 2004 to 2006 comprise the starting sample for each financial performance model before further attrition due to missing data on specified variables.

4.2 Measurement of productive efficiency and DEA

Measurement of productive efficiency can be traced back to Farrell (1957), who attempted to take actual measurements of efficiency that account for all inputs and outputs in an industry. Farrell (1957, p.254) provided a general definition of efficiency as "a firm's success in producing as large as possible an output from a given set of inputs". The essence of DEA efficiency can also be interpreted through Pareto optimality, which states that a unit is efficient only if its outputs cannot be raised without raising any of the inputs or without lowering any other outputs; likewise, a unit is also efficient only if its inputs cannot be decreased without decreasing any of its outputs or without increasing any other inputs (Charnes, Cooper and Rhodes, 1981).

DEA can assist decision making regarding productive efficiency considered important to management. Efficiency of a production unit can be estimated relative to an efficient frontier defined by benchmark production found in the sample. DEA uses linear programming to measure relative efficiency by computing a ratio of weighted sum of outputs to weighted sum of inputs. Therefore, DEA captures the interaction among multiple inputs and multiple outputs, and generates a comparative ratio for each decision-making unit (DMU) in a sample. This comparative ratio (or efficiency score) ranges between 0 and 1. DMUs assigned a score of 1 are deemed efficient in the sample while other DMUs with a score less than unity are regarded as inefficient. Such an efficiency measure is relative instead of absolute, indicating that those efficient DMUs are only efficient relative to other DMUs in the sample. That is, it is still possible that other units not included in the sample to be more efficient than the best practice DMUs in the sample.

Firstly, DEA serves as a sound framework for peer benchmarking, defining an inefficient unit by comparing it to other units within a sample, rather than trying to make a comparison to statistical averages that may not be applicable to the organisation of interest. This feature makes DEA particularly useful and attractive for bank regulators, especially when their focus is on identifying the best practices within a group of institutions. In other words, DEA is an extremal rather than an average approach (McWilliams et al., 2005).

Secondly, because DEA is a non-parametric technique, it does not require distributional assumptions. Consequently, DEA works well with a small sample size, unlike statistical and econometric approaches such as logistic regression (Premachandra et al., 2009). DEA is also not affected by collinearity in the same manner parametric techniques are.

Thirdly, DEA allows multiple inputs and outputs into a performance benchmarking model and captures their interaction in a single relative efficiency score. This characteristic is an advantage of DEA over individual ratio analysis. Gelade and Gilbert (2003) believe that a full picture of the different aspects of an organisation's efficiency cannot be obtained if only individual ratios are used. Compared to the simple ratio analysis, which provides measures from only one dimension or requires predetermined weights (e.g., the Altman's Z-score model), DEA's incorporation of multiple inputs and outputs enables multi-criteria decision making.

Fourthly, as pointed out in Premachandra et al. (2009), econometric techniques are subject to the risk of biased or deficient estimation samples. For instance, an *ex-post* sample is required to work out the parameters of an econometric model which may not be valid for a different time period. Nevertheless, if this sample is unrepresentative of the population or if researchers are unaware of its biases, the developed model is unreliable when used with an *ex-ante* sample. In contrast, the DEA technique does not require an estimation sample because the relative efficiency scores or estimates are for members of a particular sample or group only, rather than an attempt to estimate population or model parameters.

Finally, another distinct advantage of using DEA is its ability to indicate potential improvement opportunities for management. That is, DEA can inform users whether the performance of a unit can be improved relative to the observed benchmark in a peer group and by how much (not pursued in this paper).

The inputs and outputs for a DEA model can be selected by the user. This judgement can be based on experience, desired managerial focus, or literature review. In the context of financial distress assessment, this discretionary judgment brings managers, investors and regulatory agencies flexibility in designing an investigation. A higher number of variables lead to a lower discriminatory power (Dyson et al., 2001). Regarding the combination of inputs and outputs, robustness checks are important to ensure that the efficiency measures are consistent and convincing. Ultimately, to assist managers in decision making, the choice of variables in DEA models should reflect the desired perspective on performance analysis.

While the CCR (Charnes, Cooper and Rhodes, 1978) and BCC (Banker, Charnes and Cooper, 1984) models are the two original DEA models developed to measure technical and pure technical efficiency respectively, they have been superseded by more sophisticated models such as the slacks-based model (SBM) by Tone (2001). SBM inefficiencies are defined as non-radial excesses in inputs and non-radial shortfalls in outputs, whereas CCR and BCC models are both radial models that do not deal directly with non-radial inefficiencies and thus, report weak efficiency.

SBM satisfies the following technical efficiency properties:

- Acceptance of semi-positive data, that is, zero or positive numbers;
- Unit invariance that affords freedom in choosing business variables measured in various dimensions (i.e., optimal solution is not affected by variables measured in different units);
- Non-radial inefficiency measurement that accommodates non-proportional potential improvements in complex production relationships, instead of radial measurement that pre-supposes a given input (output) mix that may not be feasible;
- Non-oriented modelling of potential improvements that can simultaneously capture inefficiencies, say, on both sides of the profitability production function in a service industry (e.g., revenues and expenses for a bank); and
- Reporting efficiency in a scalar value (i.e., in a single score) that a business analyst can easily understand.

However, while the inefficient DMUs have clear rankings based on distinct scores, comparison among those efficient DMUs becomes infeasible, especially when ranking is important to a study (e.g. the current paper). As a response to this problem, Tone (2002) introduced super-efficiency with SBM. In this paper, all tests are based on the super-SBM DEA model which allows separation of tied ranks among efficient DMUs as the upper truncation of 1 is removed. Use of super-efficiency can also help in detecting potential outliers (see Banker and Chang, 2006). Avkiran (2007) proposes a conservative criterion to identify outliers where banks with super-efficiency DEA scores of 2 or above should be scrutinised as potential outliers. Thus, after the first run of the super-SBM model, any bank with a score equal to or greater than 2 can be eliminated from the sample. DEA is repeated until no outliers are found.

4.3 Test of DEA's discriminatory power

Given that DEA generates estimates of relative (peer) efficiency, where *inefficiency* may be viewed as a precursor of financial distress, the primary research question is whether *DEA peer efficiency scores are capable of flagging BHCs likely to become distressed in the near future.* To operationalize this question, it is necessary to directly compare the DEA efficiency scores of the predetermined distressed and non-distressed groups. With a super-SBM DEA model, efficient BHCs will be assigned scores greater than or equal to 1, and inefficient BHCs will be assigned scores less than 1. It is expected that non-distressed BHCs are more likely to appear as efficient, while distressed BHCs are more likely to appear as inefficient. Therefore, the primary research question can be re-stated as follows: *Are DEA peer efficiency scores for distressed BHCs significantly lower than scores for non-distressed BHCs?*

The one-tailed Wilcoxon Rank Sum test is used to determine whether there is a statistically significant difference between the distribution of the scores of distressed and non-distressed firms. If the research question is supported, then the DEA models are deemed to be effective in discriminating between these two groups of BHCs. Such an approach is consistent with Pille and Paradi (2002).

Because the motivation of this paper is to use DEA to complement credit ratings, an ideal research design would have been to compare DEA's discriminatory power with the credit ratings of BHCs. However, only a maximum of 29 out of 186 BHCs have credit ratings across some of the years. [1] While it was not feasible to make a comparison between DEA scores and credit ratings, it is appealing to apply DEA as an alternative approach to discriminating among BHCs on financial distress, particularly when credit ratings are not available.

4.4 Test of DEA's predictive power

If evidence supporting DEA's discriminatory power is found, DEA's predictive power will then be tested. The approach adapted here is the layering approach first demonstrated by Barr et al. (1994). The layering procedure is as follows:

1. After super-SBM DEA model is run for the first time, BHCs with scores of 1 or greater (i.e., efficient units) define the efficient frontier. In other words, they comprise layer 1.
2. Those efficient BHCs are then eliminated from the sample before the next run of DEA, i.e., the first layer is 'peeled off'.
3. Because the sample composition changes, the second run identifies a new set of efficient BHCs, i.e., a new layer we refer to as layer 2.
4. Steps 2 and 3 are repeated until all the remaining BHCs emerge as efficient. That is, this procedure stops when DEA can no longer discriminate among the remaining units in the sample.

[1] The unavailability of credit ratings was confirmed after consulting BankScope IT Support staff. In addition, the Compustat database was checked. Consistent with BankScope, Compustat provides no additional credit ratings. Finally, a manual search for credit ratings was conducted on S&P's, Moody's and Fitch's official websites, equally to no avail.

This layering approach is similar to credit ratings to the extent that the layers resemble the different notches of credit ratings.

A best-practice DEA model is used to predict financial distress. The best-practice DEA model, as opposed to the worst-practice DEA model, is consistent with how a DEA model is traditionally applied. In the best-practice DEA model, the intention is to identify the most efficient DMUs, that is, the best financial performers in the sample. In the context of financial distress prediction, the efficient DMUs are those furthest from distress, while the inefficient DMUs are those likely to suffer from distress in the near future.

If DEA has adequate predictive power, it is expected that the majority of healthy BHCs will be captured in the top layers. When more layers are 'peeled', the proportion of the healthy BHCs ought to fall. In other words, the ideal situation is to reveal a concentration of non-distressed BHCs in the top layers. If we were to replicate credit ratings, BHCs appearing in layer 1 would be regarded as 'financially efficient', 'healthy', and 'furthest from distress'. Therefore, they could be assigned 'AAA' level credit ratings. On the other hand, the BHCs remaining after several 'peelings' could be assigned 'below-investment-grade' credit ratings. In practice, discretion can be exercised on the proper cut-off layer to distinguish between investment and below-investment grades. Different attitudes towards risk and costs associated with portfolios can lead to varying decisions.

5. Results and analysis

5.1 Test of DEA's discriminatory power

5.1.1 CAMELS performance model

In the CAMELS model, the starting sample size was reduced from 186 to 131 because of missing observations, especially for liquid assets and loan loss reserves, and the balanced panel data requirement. That is, if a bank had a missing variable in any one year, this bank had to be excluded from the sample as we want to keep track of all banks' performances across three years (2004-2006). One potential outlier was also eliminated.

The CAMELS model tested consists of 130 banks, including 18 'failed' banks and 13 banks that received 'bailout' funds exceeding 30% of their Tier 1 capital. As anticipated, in 2006, the 'non-distressed' group has lower mean and median loan loss reserves and total non-interest expenses. However, inconsistent with literature, the 'non-distressed' group also has lower mean and median equity, net income, liquid assets and total assets. Yet the standard deviations for these four variables are lower for the 'non-distressed' group. Similar descriptive statistics are obtained when examining the 2004 and 2005 data (available from the authors).

P-values in the one-tailed Wilcoxon Rank Sum test reveal that all six variables exhibit weak or statistically insignificant discriminatory power when considered individually, with the loan loss reserve for 2006 showing the most significant one-tailed p-value of 0.0624. In unreported tables, descriptive statistics for 2004 and 2005 data reveal similar Wilcoxon test results.

5.1.2 CPM performance model

Initially, the CPM model starts with a balanced sample of 161 banks. Checks eliminate 16 banks as potential outliers, resulting in a final sample size of 144 that consists of 20 'failed', 17 'bailout' and 107 'non-distressed' banks.

Consistent with expectations of this study, in 2006, the 'non-distressed' group has lower mean and median total interest expenses and total non-interest expenses. Nevertheless, the 'distressed' group appears to be more profitable, with higher mean and median gross interest and dividend income and total non-interest operating income. Similar to the descriptive statistics for the CAMELS model, the standard deviations for all four variables in CPM are lower for the 'non-distressed' group. In unreported tables, descriptive statistics for 2004 and 2005 data show similar patterns.

P-values in the one-tailed Wilcoxon Rank Sum test suggest, once again, weak or insignificant discriminatory power for each of the four variables in 2006 CPM. While the 2005 data also show similar results to the 2006 data, the 2004 data generate particularly insignificant p-values. This paper will demonstrate that, whereas individual variables fail to distinguish between 'distressed' and 'non-distressed' banks, the multi-dimensional simultaneous optimization by DEA provides discriminating measurements.

5.1.3 DEA's discriminatory power

Having specified the input and output variables in the CAMELS and CPM models, super-SBM DEA is executed. Both the CAMELS and CPM models report statistically significant p-values when used in DEA. With a 1% level of significance, the research question is supported when 2006 data are used in both models. Using the 2005 data, the research question is also supported at the 5% and 10% levels of significance in the CPM and

CAMELS models, respectively. Overall, profitability, which is the main focus of CPM, seems to be an important factor in differentiating the 'distressed' and 'non-distressed' groups. Namely, any bank that is capable of maximising its revenues while minimising its costs up to three years prior to the GFC is more likely to maintain its financial health during the GFC. The DEA scores of the CAMELS model that capture six different financial aspects of a bank gradually lose discriminatory power as we use data more distant from the GFC.

5.2 Test of DEA's predictive power

5.2.1 CAMELS performance model

After examining DEA's discriminatory power, we proceed to explore its predictive power, i.e., its ability to identify those BHCs likely to be distressed through efficiency estimates. When best-practice DEA is used, it is expected that the majority of efficient banks appearing in layer 1 will belong to the 'non-distressed' group as these efficient banks are capable of maximising their equity, liquid assets, total assets and net income, while minimising their total non-interest expenses and loan loss reserves. It is also expected that as each layer's cohort of efficient BHCs are removed, the proportions of distressed versus non-distressed BHCs on following layers will converge. Because the CAMELS model reveals statistically significant discriminatory power using 2005 and 2006 data, we now investigate the composition of its individual layers with data only from these two years. With more recent data, that is, data closer to the GFC, the model is expected to perform better in capturing 'non-distressed' banks in top layers and 'distressed' banks in bottom layers.

Tables 1 and 2 report the composition of layers when efficient frontiers are sequentially removed. The majority (90.48%) of banks captured in layer 1 belong to the 'non-distressed' group; the remaining 9.52% are the 'bailout' banks. After elimination of all banks captured in layer 1, DEA is rerun to examine the new frontier, i.e., layer 2. In layer 2, the percentage of 'non-distressed' banks captured drops to 75%. Compared to layer 1, more 'distressed' banks populate layer 2. This finding is consistent with the expectation that the 'non-distressed' banks are likely to be found in the top layers, whereas 'distressed' banks will appear in the bottom layers. When examining the composition from layers 1 to 6, an overall decreasing trend is observed for the percentage of 'non-distressed' banks captured. In other words, the percentage of 'distressed' banks captured on the next efficient frontier increases when more of the benchmark performers are removed from the sample.

[Place Table 1 about here]

Results from the 2005 data do not show an equally clear trend across layers (efficient frontiers) although, once again, the non-distressed group dominates the layers in each DEA run. In Table 2, while none of the 'failed' banks are captured and 91.3% of 'non-distressed' banks are identified as financially efficient in layer 1, there is no obvious trend across the layers in the percentage of either the 'distressed' or 'non-distressed' banks.

[Place Table 2 about here]

5.2.2 CPM performance model

Because the CPM model possesses discriminatory power across 2004-2006 data, we now examine their predictive power in a similar fashion to that of CAMELS. Table 3 reveals that none of the 'failed' banks are included in the efficient frontier in layer 1, but the proportion of failed banks increases to 30% by layer 7. No clear trend is shown for the percentage of 'bailout' banks captured. Generally speaking, from the top to the bottom layers, the number of 'failed' banks captured increases and the number of 'non-distressed' banks captured decreases, as anticipated earlier.

In unreported tables, the CPM model that uses 2005 data provides similar results to the 2006 test. However, the 2004 results do not show a clear trend in percentages of 'failed' or 'non-distressed' banks, although the majority of BHCs on frontiers are still non-distressed except in layer 7 where there is an equal split. This finding is understandable as the predictive power of DEA diminishes with financial data that are further removed from the GFC.

[Place Table 3 about here]

Notably, for the 'bailout' banks, neither the CAMELS nor the CPM model reveals a distinct pattern.

5.2.3 A second look at predictive power through cumulative percentages

The results reported so far provide a general overview of the success of DEA as a predictive technique where we observe that the efficient frontiers are dominated by non-distressed BHCs – thus highlighting the relationship between efficiency and financial health. Focusing on the cumulative percentage of each group may help decision makers to determine a cut-off layer.

Table 4 replicates the essence of Paradi et al.'s (2004) main test of DEA's predictive power. However, Paradi et al. (2004) applied the worst-practice DEA, while the current paper is based on the best-practice DEA. In other words, Paradi et al. would expect to capture bankrupt firms in top layers, while we expect to see 'distressed' banks in bottom layers. Thus, the calculation of the cumulative percentage of each group starts from the bottom layer, with an expectation that the bottom layers would capture more 'distressed' banks than the top layers. With such an expectation, users need only to focus on the bottom layers (e.g., layers 6, 5, 4 and so on) when seeking to identify the majority of 'distressed' banks. Using the 2006 data, 5.56% of a total of 18 'failed' banks are captured in layer 6. When moving to layer 5, a cumulative percentage of 27.78% of 'failed' banks are captured. The great majority (72.22%) of 'failed' banks are captured by layer 3. The 'bailout' or the 'distressed' group can be interpreted in a similar way.

[Place Table 4 about here]

In practice, depending on the user's risk attitude and aggressiveness, discretion can be exercised in deciding on an appropriate cut-off layer. If a user is very concerned about bank failure, only those banks that appear on the very top layer can escape examination (i.e. layer 2 is the cut-off layer). In addition, the trade-off between Type I and Type II errors can also be a concern. For example, when one can only accept a low Type I error, there is a higher chance of having a large Type II error. For bankruptcy studies, FDIC (2011) indicates that this trade-off between Type I and Type II errors is inherent in all forecasts regardless of the estimation method. The FDIC also mentions that it is difficult to capture problem banks well in advance in the real world, even when an effort is made to identify risk factors.

In the context of this paper, Type I errors involve misclassifying distressed banks as non-distressed, whereas Type II errors involve identifying non-distressed as distressed. For instance, to capture all of the 18 'failed' banks out of a total of 130 banks, 109 banks must be examined up to layer 2. This process minimizes the Type I error but inevitably leads to the consumption of extra resources as more banks are investigated. Likewise, banks captured in layer 1 would be the main focus for risk-averse investors. However, risk-takers might be willing to invest in banks in lower layers.

In an unreported table, results from the 2005 CAMELS test reveal similar predictive power. Failure prediction of 100% can be achieved in layer 2, while the cumulative percentage of 'non-distressed' and 'bailout' banks captured in this same layer is 78.79% and 84.62%, respectively. In short, all 'failed' banks can be successfully captured from the bottom to layer 2 in both 2006 and 2005 CAMELS tests. About half of 'distressed' banks are captured in the three bottom layers, supporting DEA's predictive power.

The 2006 CPM test reports better results than the 2006 CAMELS test (see Table 5). That is, the cumulative percentage of 'failed' banks captured in layer 6 and 7 by the 2006 CPM is higher than that of the 2006 CAMELS. To capture a total of 20 'failed' banks out of 144 banks in the sample, layer 7 to layer 2 have to be examined for the 2006 CPM test, without examining the 26 banks in layer 1. When the examination concludes in layer 2, in addition to capturing all 'failed' banks, both the 2006 CAMELS and CPM tests capture about 81% of 'non-distressed' banks; that is, they have similar prediction errors. Unreported results from both the 2005 and 2004 CPM tests suggest similar patterns. However, 95%, as opposed to 100%, of 'failed' banks are captured up to layer 2 in the 2005 CPM test.

[Place Table 5 about here]

To conclude, the 2004 to 2006 CPM tests all support DEA's predictive power (2004 and 2005 results are available on request). Profitability is certainly an essential factor that contributes to studies of financial distress in banks. However, for the 'bailout' banks, on average about 76% of them are captured when layer 2 is reached in the 2004 to 2006 CPM tests. Thus, the predictive power of DEA is more evident with the 'failed' group (consisting of banks having the most severe outcome of financial distress).

6. Robustness Checks

6.1 Consistency of the CAMELS and CPM models across time

Composition of the efficient frontier should not vary substantially across consecutive years because DEA scores of 'distressed' banks are significantly lower than scores of 'non-distressed' banks. Overall, we find that DEA produces consistent information over the two years as the great majority of efficient banks (19 out of 21 for CAMELS, and 19 out of 26 for CPM) appear in both years' frontiers, indicating that observed efficiencies are not one-off events limited to a year.

While layer 1 captures financially efficient banks under best-practice DEA, the bottom two layers typically focus on inefficient banks, i.e., 'distressed' banks. Examination of the bottom two layers is necessary to see whether the 'distressed' banks are consistently captured. Although the composition of the captured 'distressed' banks may change, if the variation is small, we would be further assured that DEA can flag 'distressed' banks correctly two years in advance.

We find that the 2005 CAMELS test can successfully capture 5 out of 6 'distressed' banks identified by the 2006 CAMELS test. A stricter test of consistency is to use Spearman's rank correlations. Using super-efficiency DEA scores from both the 2006 and 2005 CAMELS tests, the ranks of all banks are correlated at 0.6627, with a two-tailed significance of 0.0000, supporting the contention that DEA results are consistent. Hence, in the CAMELS model, 'distressed' banks can be flagged up to two years in advance. Users of DEA could therefore implement timely measures to avoid bank distress in the near future.

Similar results are observed for the CPM model but with a warning for 2004 (details are available from the authors). That is, with the CPM model, predictive power based on earlier financial data (e.g., 3 years in advance) is not as reliable or consistent as the 2005 and 2006 tests. Thus, the 2004 CPM results should be interpreted with care as they may be subject to changes in the near future. In summary, both the CAMELS and CPM models generate consistent information using 2005 and 2006 data where considerable predictive power two years in advance of the global financial crisis has been observed.

6.2 Stability of the efficient frontier to data perturbations

In this sub-section, the objective is to examine whether model specification affects stability of DEA results. Thus, we monitor the membership of the efficient frontier as variables are systematically deleted because any substantial change of the frontier is likely to cause re-ranked inefficient BHCs. The tests are executed independently for each financial performance model and for each year. Following Avkiran (2007), the procedure is as follows:

1. For each financial performance model, one input or output variable is deleted before running DEA;
2. The new frontier obtained is recorded and compared with the original frontier when all variables in a model are used, i.e., the full-complement model;
3. Steps 1 and 2 are repeated after the deleted variable is returned to the model, thus maintaining the same degrees of freedom for each test;
4. The tests are executed until all variables in a model have been individually removed from the sample. For example, there are six new frontiers in the CAMELS model due to its six variables, while there are four new frontiers for CPM.

In determining the stability of the efficient frontier of each model, Avkiran (2007) states that the efficient frontier can be regarded as stable if no new banks are found on the new frontiers when any one variable is deleted. Overall, the 2004 to 2006 CPM tests exhibit stability in their frontiers as no new banks are captured beyond those captured by the full-complement model. Regarding CAMELS, while the 2005 and 2006 frontiers are also stable, the deletion of net income and the deletion of total assets both result in the same new bank being identified in the 2004 model. Despite this minor change in frontier membership, overall, tests support DEA's stability in both the CAMELS and CPM models over the 3 years preceding the GFC.

6.3 Use of market variables

We propose two market-based models where two new variables substitute for variables used in both the CAMELS and CPM models. Comparison is made between CAMELS (original) and CAMELS (mkt) and between CPM (original) and CPM (mkt). The two CAMELS and two CPM models are based on the same smaller samples, namely, N=117 and N=105 respectively, thus any difference found can be attributed to the changed variables as explained below:

- CAMELS (mkt): Replace the outputs of net income and total assets with annual stock return for each calendar year and market capitalisation at each calendar year-end;
- CPM (mkt): Replace the outputs of total non-interest operating income, and gross interest and dividend income, with annual stock return and market capitalisation for each calendar year.

Once again, we note that neither the annual stock return nor the market capitalisation variable is able to discriminate between the 'distressed' and 'non-distressed' groups when used individually. On the other hand, DEA results show that the introduction of market variables does not improve the discriminatory power of the two models. In the CAMELS (mkt) model, p-value (Wilcoxon Rank Sum test) from the 2006 test is significant at the 10% as opposed to the 5% for the CAMELS (original) model. This deterioration is more evident in the two CPM models. While p-values from the 2004 to 2006 tests in the CPM (original) model are all significant (at least at the 10% level), no significant result is found with the CPM (mkt) model.

Thus, a comparison of predictive power between CPM (original) and CPM (mkt) is not attempted because the CPM (mkt) model lacks discriminatory power. Regarding the predictive power of the two CAMELS models, unreported results show that both models successfully capture a cumulative percentage of 84.52% of the 'distressed' banks by layer 2.

In summary, the introduction of market variables has either no impact or a negative impact. The market-oriented model significantly *under-performs* the original CPM model on discriminatory power, whereas the CAMELS (mkt) model emerges with a predictive power similar to that of the original model. These results add more confidence to our original choice of inputs and outputs because the market-based models do not perform any better.

6.4 Can parametric techniques be applied to DEA performance models in this study?

The purpose of this section is to find out if alternative parametric techniques can predict financial distress in BHCs using the same performance models in this study. For example, linear discriminant analysis is well-established in distress or bankruptcy analysis (see seminal work by Altman 1968 and Altman et al 1977). In the current study, it may be used in deriving a classification model that can distinguish between distressed and non-distressed BHCs. Essentially, we use discriminant analysis to address the original primary research question of whether *DEA peer efficiency scores are capable of flagging BHCs likely to become distressed in the near future.* In order to make the non-parametric versus parametric comparison meaningful, we work with the same set of variables in the CAMELS and CPM performance models, which were, in turn, selected based on literature.

In this study, stepwise discriminant analysis is initially used with the objective of identifying those predictor variables making significant contributions to distinguishing between BHCs on financial performance. In the absence of any theoretical justification for giving priority to certain predictors, it is appropriate to allow statistical criteria to determine the most useful discriminating variables (Klecka 1982). We start discriminant analysis with the sample of BHCs that have been separated into sub-groups 'distressed' and 'non-distressed' according to the three distress criteria. These form the banks of known group memberships to be used for deriving discriminant functions using 2005 and 2006 data. The yearly data are split into estimation and validation samples by first ranking the sample on size (proxied by average assets) and then selecting every second bank to create a sub-sample. This approach creates two sub-samples for each year where banks are highly comparable on size of operations. Six independent variables representing CAMELS and four independent variables representing CPM enter stepwise discriminant analysis.

Testing reveals that none of the performance models that actually work with DEA result in a discriminant function. While this can be explained by collinearity among the variables and near-unity Wilks' lambda values, more importantly, it highlights the advantage of non-parametric DEA over regression-like parametric techniques. DEA's ability to discriminate using correlated and non-normally distributed variables that are included in a performance model based on theory or managerial discretion makes it a more versatile and forgiving technique.

7. Concluding remarks

This paper develops an application of DEA to predict financial distress in bank holding companies in the period leading up to the recent global financial crisis. An *ex-post* sample is used to investigate DEA's discriminatory and predictive power when the models are based on 2004, 2005, and 2006 financial data. Instead of arbitrarily selecting input and output variables, this paper uses two financial performance models (CAMELS and CPM) based on prior literature to predict financial distress. The results for both the CAMELS and CPM models support DEA's discriminatory and predictive power, suggesting that users can rely on DEA results generated from financial data up to 2 years prior to the crisis. Moreover, the CPM model outperforms the CAMELS model, implying that profitability is a key factor in predicting financial distress in banks. Observing no discriminatory power when the variables comprising CAMELS and CPM models are used individually lends further creditability to the potential of DEA as a multi-criteria, predictive technique.

In robustness checks, a number of independent tests are executed. For example, results are consistent across two years prior to the GFC and DEA is not sensitive to deletion of variables. The introduction of market variables has a negative impact on discriminatory power of DEA. The market-oriented CPM model under-performs the original model on discriminatory power. On the other hand, the CAMELS (mkt) model emerges with a predictive power similar to that of the original model. Overall, these results support our original choice of inputs and outputs because the market-based models do not out-perform. Linear discriminant analysis using the same variables in our two performance models fails, highlighting the ability of DEA to work with correlated variables where well-established parametric techniques may not produce results.

From an *ex-post* standpoint, this paper contributes to the literature by demonstrating DEA's discriminatory and predictive power and, equally importantly, its robustness to alternative model specifications. In cases where credit ratings are not available, regulatory agencies, managers, and investors can rely on DEA because the technique is able to rank banks on inefficiency which has been shown to correspond to financial distress.

For regulatory agencies, DEA can be used as a preliminary off-site screening tool to detect potentially distressed banks as opposed to an on-site examination process, which is more costly and time consuming. In addition, because regulatory agencies' have easier access to financial data on banks, a larger sample can be obtained from which best-practice DEA can identify healthy banks that appear in the top layer. Attention can then be given to potentially distressed banks captured in the bottom layers as they are candidates for on-site examination and close monitoring. If DEA is regularly used on an annual basis, regulatory agencies can also keep track of how those distressed banks improve relative to their past performance.

For managers who make strategic decisions on banks' operations, knowing the likelihood of financial distress in the near future and their current standing among competitors, are fundamental to long-term survival. For example, DEA can be considered by managers as a useful source of information on potential improvement opportunities (for brevity, not demonstrated in this paper). That is, DEA explicitly tells managers by how much resources can be reduced and higher outputs can be set. DEA also identifies peer banks that operate at a benchmark level of efficiency, that is, those institutions furthest away from financial distress. All this information can be obtained in a quick and easy manner, allowing managers to spend more time on other key business activities such as market penetration and increasing customer loyalty.

For investors, best-practice DEA provides information on how risky an investment in a particular bank could be. Banks captured in the top layers are typically suitable for risk-averse investors, because these banks are unlikely to incur financial distress at least within two years. Some risk takers may invest in banks captured in the bottom layers to seek potentially higher returns but with greater volatility. Investors can therefore gather information themselves without paying and waiting for recommendations from brokers.

In conclusion, DEA may be useful in assisting regulatory agencies, managers, and investors in making economic decisions. It is a widely-used relative, multi-criteria performance evaluation technique that could complement or substitute for the often criticized credit ratings. In this paper, due to unavailability of credit ratings in our sample, comparison between credit ratings and DEA results was not feasible – something that can be followed up in future studies. In addition, since this paper reports some sensitivity to the introduction of market-based variables, such issues can also be examined further.

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Table 1 : Composition of each layer (frontier) in CAMELS 2006

	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5	Layer 6
Failed captured (%)	0.00	17.86	10.81	14.81	26.66	50.00
Bailout captured (%)	9.52	7.14	8.11	18.52	6.67	0.00
Sub-total, distressed (%)	9.52	25.00	18.92	33.33	33.33	50.00
Non-distressed captured (%)	90.48	75.00	81.08	66.67	66.67	50.00
Total (%)	100	100	100	100	100	100

The numbers reported represent the percentage of 'failed', 'bailout' and 'non-distressed' banks that comprise each individual layer. For example, examining bank membership in layer 1 reveals 90.48% of banks captured on the frontier belong to the 'non-distressed' group.

Table 2: Composition of each layer (frontier) in CAMELS 2005

	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5	Layer 6
Failed captured (%)	0.00	20.00	17.24	8.70	21.43	16.67
Bailout captured (%)	8.70	11.43	10.34	13.04	7.14	0.00
Sub-total, distressed (%)	8.70	31.43	27.58	21.74	28.57	16.67
Non-distressed captured (%)	91.30	68.57	72.42	78.26	71.43	83.33
Total (%)	100	100	100	100	100	100

The numbers reported represent the percentage of ‘failed’, ‘bailout’ and ‘non-distressed’ banks that comprise each individual layer. For example, examining bank membership of layer 1 reveals 91.30% of banks captured on the frontier belong to the ‘non-distressed’ group.

Table 3: Composition of each layer (frontier) in CPM 2006

	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5	Layer 6	Layer 7
Failed captured (%)	0.00	8.33	16.00	16.67	15.79	21.43	30.00
Bailout captured (%)	19.23	8.33	12.00	8.33	15.79	7.14	10.00
Sub-total, distressed (%)	19.23	16.66	28.00	25.00	31.58	28.57	40.00
Non-distressed captured (%)	80.77	83.34	72.00	75.00	68.42	71.43	60.00
Total (%)	100	100	100	100	100	100	100

The numbers reported represent the percentage of 'failed', 'bailout' and 'non-distressed' banks that comprise each individual layer. For example, examining bank membership of layer 1 reveals 80.77% of banks captured on the frontier belong to the 'non-distressed' group.

Table 4: Cumulative percentage of 'distressed' banks captured – CAMELS 2006

	Layer 6	Layer 5	Layer 4	Layer 3	Layer 2	Layer 1
Cumulative % of failed captured	5.56	27.78	50.00	72.22	100.00	-
Cumulative % of bailout captured	0.00	7.69	46.15	69.23	84.62	100.00
Cumulative % of distressed captured	3.23	19.35	48.39	70.97	93.55	100.00
Cumulative % of non-distressed captured	1.01	11.11	29.29	59.60	80.81	100.00

Since the intention is to capture 'distressed' banks, results are displayed from the very bottom, layer 6, to the very top, layer 1. Layer 6 captures 5.56% of the 'failed' banks, i.e. 5.56% x 18 = 1 out of a total of 18 'failed' banks is captured. Thus, this table allows users to decide which layer could be an appropriate cut-off layer.

Table 5: Cumulative percentage of 'distressed' banks captured – CPM 2006

	Layer 7	Layer6	Layer 5	Layer 4	Layer 3	Layer 2	Layer 1
Cumulative % of failed captured	20.00	35.00	50.00	70.00	90.00	100.00	-
Cumulative % of bailout captured	5.88	11.76	29.41	41.18	58.82	70.59	100.00
Cumulative % of distressed captured	13.51	24.32	40.54	56.76	75.68	86.49	100.00
Cumulative % of non-distressed captured	6.54	15.89	28.04	44.86	61.68	80.37	100.00

Results are displayed from the very bottom, layer 7, to the very top, layer 1. Layer 7 captures 20% of the 'failed' banks, i.e. 20% x 20 = 4 out of a total of 20 'failed' banks are captured.