Bournemouth University

BAFES –

Bournemouth Accounting, Finance & Economic Series

NO 12 / 2017

To Be Bailed Out or To Be Left to Fail? A Dynamic Competing Risks Hazard Analysis

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Abstract

During the late 2000s financial crisis, a large number of banks either failed or received financial aid thus inflicting substantial losses on the system. We contribute to the early warning literature by developing a dynamic competing risks hazard model that explores the joint determination of the probability of a distressed bank to face a licence withdrawal or to be bailed out. The underlying patterns of distress are analysed based on a broad range of bank-level and environmental factors. We find that institutions with inadequate capital, illiquid and risky assets, poor management, low levels of earnings and high sensitivity to market conditions have a higher probability to go bankrupt. Bailed out banks, on the other hand, face both capital and liquidity shortages, experience low earnings, and are highly exposed to market products; however, neither managerial expertise, nor the quality of assets are relevant to the odds of bailout. We further document that large and complex banks are less likely to fail and more likely to be bailed out and that authorities are more prone to provide support to a distressed bank, which is well-connected with politicians and political parties and less prone to let it go bankrupt. Importantly, our model outperforms the commonly used logit model in terms of forecasting accuracy in all the in- and out-of-sample tests we conduct.

JEL Classification: C13; C53; D02; G01; G21.

Keywords: Financial crisis; Bailout; Failure; Dynamic competing risks hazard model; Forecasting.

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1. Introduction

During the global financial crisis, a large number of banks worldwide either failed or received financial aid by national authorities thus inflicting substantial losses on the system. In the U.S., more than 500 collapses have been reported from the outbreak of the crisis in mid-to-late 2007 through the early days of 2016. The Federal Deposit Insurance Corporation (FDIC) has been appointed receiver of all the bankrupt institutions and this has incurred a total loss of $74 billion.[1] In a similar vein, a costly and far-reaching rescue plan was implemented in the U.S. financial services industry shortly after the outbreak of the crisis. Almost immediately after the collapse of Lehmann Brothers in mid-September 2008, the U.S. Congress passed the Emergency Economic Stabilization Act (EESA) and authorised the Department of the Treasury to launch the Troubled Asset Relief Program (TARP). Under TARP, the Treasury established the Capital Purchase Program (CPP) which was designed to purchase up to $250 billion of preferred stocks and equity warrants from the qualifying undercapitalised banks with the utmost purpose to stabilise the banking system.

From an economic viewpoint, the recapitalisation of banks doubled with the cost of failures and that of the large stimulus programmes which national governments launched to revive demand led to the explosion of public debt in many advanced economies around the globe. Laeven and Valencia (2012) highlight that episodes of banking crises result in a 23% cumulative output loss as well as substantial increases in fiscal debt. Fiscal problems are to a great extent responsible for the observed upsurge in sovereign risk in a number of economies around the globe, which put a further upward pressure on countries' borrowing costs undermining -in some cases- the value of their currencies. Within this context, several borrowed countries still face considerable difficulties in repaying their loans or obtaining new loans from the markets as they have been locked out from them. By contrast, a well-functioning and robust banking sector strengthens the stability of the entire financial system and is a crucial determinant of economic growth. Therefore, the need for the development of an early warning system capable to predict bank distress has again come to the forefront in the relevant literature which dates back to Meyer and Pifer (1970), Sinkey (1975), Martin (1977), and Pettway and Sinkey (1980).

We contribute to the revival of the early warning literature by designing a system which, apart from capturing the early bankruptcy signals, it also detects the early warnings for distressed

[1] Source: https://www5.fdic.gov/hsob/SelectRpt.asp?EntryTyp=30&Header=1

banks which are likely to need financial support in case of a financial debacle. That is, the term 'distress' incorporates both the concept of bank failure and that of bailout, which, both imply a considerable burden on governments and tax payers. The two distress events are treated as competing events in our analysis. We, therefore, construct a competing risks hazard model where the two events are likely to occur. This is the first time that such a dual early warning system of distress is developed in the relevant literature. An additional innovative feature of our paper is that the empirical analysis is conducted within the dynamic framework proposed by Shumway (2001), which allows the distress probability assigned to each bank to vary with time. Notwithstanding its attracting features (which are discussed in detail later), the Shumway approach has been only marginally applied in the banking literature. Importantly, we explore and analyse the underlying patterns of distress based upon a broad range of observable and non-observable determinants: the financial ratios that regulators apply to rate bank performance and soundness, a set of systemic importance indicators, a group of key bank characteristics, and a set of control variables related to macroeconomic and financial conditions as well as to the bank regulatory environment.

We rely on our empirical findings to sketch out the profile of the failed and bailed out banks. Institutions with inadequate capital, illiquid and risky assets, poor management, low levels of earnings and high sensitivity to market conditions have a higher probability to go bankrupt. Bailed out banks, on the other hand, face both capital and liquidity shortages, experience low earnings, and are highly exposed to market products; however, neither the expertise of bank managers, nor the quality of bank assets are relevant to the odds of bailout. We further document that large and complex banks are less likely to face a license withdrawal and more likely to be bailed out by the authorities, providing strong evidence on the occurrence of the Too-Big-To-Fail (TBTF) and the Too-Complex-To-Fail (TBTF) phenomena in banking. Moreover, authorities are more prone to provide support to a distressed bank, which is well-connected with politicians and political parties and less prone to let it go bankrupt. Taken together, the effects of the groups of bank-specific and environmental variables that we employ in our analysis confirm that the determinants of bank failures and those of bailouts differ from each other to a considerable extent, showing that the authorities treat a distressed bank differently in their decision to let it fail or to bail it out. Importantly, our hazard model outperforms the commonly used logit model in terms of forecasting power in all the in- and out-of-sample tests we conduct.

The rest of the paper is organised as follows. Section 2 reviews the key studies on early warning systems in the banking literature. Section 3 presents how the dynamic competing risks hazard model is developed, and describes our data and the model variables. Section 4 discusses the in-sample estimation results and compares the out-of-sample prediction ability of our model with that of the logit model. Section 5 is devoted to the robustness analysis, and Section 6 concludes summarising the major findings of the paper.

2. Related literature

There is a broad literature on early warning signals of bank failure, which can be traced back to the early 1970s. A strand of this literature takes a microeconomic approach focusing on individual bank characteristics, whereas a second strand explains the occurrence of banking crises in a single- or, most of the times, multi-country setting from a macroeconomic viewpoint relying on institutional, legal, regulatory and other environmental variables.[2] In what follows, we review the key studies that fall into the former literature strand, as this is the strand into which our study fits.

Several different empirical methodologies have been utilised to predict bank failure. In their seminal work, Meyer and Pifer (1970) apply multiple discriminant analysis to identify the variables that can be used to discriminate between failed and sound banks and also to predict bankruptcy. They include a number of performance and risk-related accounting measures in their analysis and show that even though embezzlement and other financial irregularities may have an impact on bankruptcy, accounting information can reliably discriminate bankrupt from solvent institutions. Sinkey (1975) also conduct a discriminant analysis confirming that balance sheet and income statement measures are reliable discriminators between problem and non-problem banks. In a similar empirical context, Pettway and Sinkey (1980) rely on a sample of 33 large banks with actively-traded securities that failed over the period 1970-1975 to develop an early warning system that uses both accounting and market information. More recently, Cox and Wang (2014) resort to discriminant analysis to identify U.S. bank failures during the 2007-8 crisis. They provide evidence that illiquid loans and the exposure of banks to the interbank funding markets constitute the main predictors of failure.

[2] Examples of early warning macroeconomic studies are those of Demirgüç-Kunt and Detragiache (2005), Davis and Karim (2008), Schularick and Taylor (2012), and Lang and Schmidt (2016). A comprehensive survey of the relevant empirical literature is provided by Kauko (2014).

Martin (1977) conducts a discriminant analysis supported by a logit model focusing on 58 bank failures which occurred between 1970 and 1976. The study concludes that the relevance of financial indicators in predicting failures varies over the business cycle: it increases during periods of stress, and decreases during economic upturns. Espahbodi (1991) also provides evidence for the ability of logit and discriminant models to identify the potential failures based on a set of financial ratios for 48 banks that failed in 1983 and for 48 matching solvent banks. Gonzalez-Hermosillo et al. (1997) focus on the Mexican crisis of the mid-90s to construct an index of bank fragility based on a logit model. Kolari et al. (1996) and Kolari et al. (2002) use the logit model together with the nonparametric trait recognition technique to conduct an assessment of bankruptcies in the U.S. banking industry. Lanine and Vennet (2006) also apply the logit model and a trait recognition approach to a set of Russian commercial banks to assess what types of banks are vulnerable to shocks and whether or not bank-specific characteristics can be utilised to predict vulnerability to failures. Cole and Gunther (1998), on the other hand, forecast bank failures applying a standard probit model to bank accounting data, whereas Crowley and Loviscek (1990) classify failures amongst small U.S. commercial banks that took place in 1984 using linear probability, logit, probit, and discriminant models. In a similar vein, Canbas et al. (2005) combine the principal component analysis with discriminant analysis, probit and logit techniques to construct an integrated early warning system that can be utilised as a regulatory tool for the detection of banks that experience financial difficulties.

More recently, Poghosyan and Cihak (2011) rely on a logistic regression analysis to examine bank distress in 25 EU countries. In the same modelling environment, DeYoung and Torna (2013) show the importance of non-interest income activities, such as securities brokerage, investment products and asset securitisation to the failure likelihood of U.S. banks in the 2007-8 crisis, whereas Distinguin et al. (2013) use a sample of major listed banks from eight East Asian economies to show that both accounting and market measures are effective indicators of bank failures. Berger et al. (2016) also resort to data from the recent crisis to examine the roles of ownership, management, and compensation structures in U.S. bank failures applying a multivariate logit model. Other recent studies that also resort to logistic probability models to predict failures in the U.S. banking industry are those of Jin et al. (2011), Cole and White (2012), and Lu and Whidbee (2013).

Various intelligent techniques based on neural networks (e.g., Quek et al., 2009), decision trees (e.g., Ioannidis et al., 2010), and hybrid methodologies (e.g., Ng et al., 2008) mainly inspired by the operations research literature have been also applied to signal failure in the banking industry.[3] Calabrese and Osmetti (2013) proposes the generalised extreme value model as a new empirical approach that can be particularly suitable for predicting binary rare events data, i.e., when the observed number of ones in the sample under scrutiny is very low. The approach is adopted by Calabrese and Giudici (2015) in the context of the early warning banking literature. The study is focused on the Italian banking sector, defining failure either as a default or as a merger or acquisition. It documents that the Basel III capital requirements are crucial determinants of bankruptcy, while macroeconomic factors are relevant only in the events of mergers or acquisitions. Calabrese et al. (2017) extend the aforementioned approach by proposing the longitudinal binary generalised extreme value model, which they utilise to explore how and to what extent TARP reduces the failure probability of the U.S. commercial banks accounting for a set of macroeconomic and idiosyncratic factors. Their results show that several financial ratios which are identified in the relevant literature as playing a key role in the performance and risk-taking behaviour of banks together with personal income growth rate can be used to predict distress, and that TARP provides only a short-term relief for banks.

The early warning literature also employs the Cox (1972) proportional hazard model in the assessment of the drivers of bank failures. Cox model is semi-parametric in contrast to logit or probit models which are purely parametric. In the Cox modelling environment, the usual likelihood function is replaced by the partial likelihood function. Hence, statistical inference is similar to that in logit and probit models and has asymptotic properties similar to those based on the standard likelihood. Lane et al. (1986) offer the first application of the Cox model to the prediction of bank failures. By focusing on a sample of U.S. commercial banks that failed between 1979 and 1984, they find strong evidence about the usefulness of the model in providing the authorities with the likely time to failure. Whalen (1991) also relies on a set of U.S. banks to show that the Cox model has a high overall classification accuracy and that it can flag a considerable proportion of failures early. Similarly, Wheelock and Wilson (1995) use the Cox model to examine the probability of bank failures and the characteristics of the banks that

[3] Kumar and Ravi (2007) and Demyanyk and Hasan (2010) provide a comprehensive review of these applications.

fail and those that survive conducting a historical analysis that relies on the collapse of commodity and real estate prices in the 1920s. Molina (2002) refer to the Cox hazard model to estimate the time-to-failure of the Venezuelian banks as a function of a group of bank-specific factors.

In the wake of the recent crisis, a few studies have turned to apply hazard modelling techniques to predict bank failure. Fiordelisi and Mare (2013) examine the relevance of cost, revenue and profit efficiency as well as that of capital adequacy in the estimation of the default probability of Italian cooperative banks. They find that higher levels of efficiency and capital are positively related with the probability of survival, supporting the view that stronger capital buffers provide additional loss absorbency and reduce moral hazard problems. Ng and Roychowdhury (2014) analyse the incremental link between the failure probability and the add-back component of the loan loss reserves as regulatory capital. Their results suggest that add-backs are positively associated with failure and that this relationship holds in cases in which the add-backs are very likely to increase a bank's total regulatory capital. Mare (2015) is focused on Italian cooperative banks using annual financial statements and a set of macroeconomic variables over the period 1993-2011 to compute the hazard rate separately for bankrupt institutions and for those subject to merger, acquisition, and voluntary closure based on the Shumway model. His results show that bank failure is better captured when we account for the state of the economy both at the national and the regional levels and that voluntary closures and acquisitions are linked to bank distress.

The studies of Wheelock and Wilson (2000) and Brown and Dinc (2011) extend hazard analysis by proposing a competing risks hazard modelling approach, which considers mergers and acquisitions as competing the event of failure. Focusing on a sample of banks with more than $50 million of assets and use quarterly data from 1984q3 through 1993q4, Wheelock and Wilson (2000) suggest that the financial ratios which are used by regulators to rate bank performance and soundness are important determinants of both mergers and failures and that the competing hazard of merger is less likely when capital and earnings are higher. Brown and Dinc (2011) rely on a data set that consists of 21 emerging market economies to show that a distressed bank is less likely to be merged with or acquired by another bank or closed by the authorities if other banks in the examined market are weak. They, hence, document a Too-Many-to-Fail channel of regulatory forbearance in a multi-country bank setting.

3. Empirical Analysis

3.1. Data

We focus on the U.S. commercial and savings banking institutions that file a Report on Condition and Income (also known as Call Report). Following the relevant studies (see Cole and White, 2012; Cornett et al., 2013; Li, 2013; Berger et al., 2016), we exclude thrifts -i.e., savings and loans associations- from our empirical analysis because they file a different report (the Thrift Financial Report).[4] Another important reason that justifies the exclusion of these institutions is that they operate under a different charter. A bank charter largely determines the activities a bank is allowed to engage in, the specific regulations it is subject to, and the costs it may have to incur in case of failure. Even though the main business of thrift institutions is similar with that of commercial and savings banks as they all accept deposits and make loans, thrifts are traditionally designed to serve U.S. consumers rather than corporates. In specific, they are specialised in mortgages and real estate lending and are required to have 65% of their lending portfolio tied up in consumer loans. Additionally, thrifts have a significant advantage over commercial and savings banks: they can borrow money from the Federal Home Loan Bank System at a low interest rate, which translates into higher rates of interest on savings accounts at thrifts as compared to other types of banks. Importantly, thrifts do not offer the range of financial services that is typically offered by commercial and savings banks, implying that their income sources and the relevant risks are not always comparable.

Our data are of quarterly frequency and extend from the beginning of 2003 (2003q1) to the end of 2009 (2009q4), which is the quarter when TARP was completed. Indeed, banks that applied for TARP money and received preliminary approval should have completed funding by December 31, 2009. Importantly, no considerable regulatory or other relevant reforms occurred in the U.S. banking sector during the examined time period, implying that the sector remained largely unaffected by exogenous factors. If any reforms had taken place during our sample period, they could have biased our results as it is well established in the literature that regulation strongly affects industry structure and alters the behaviour of banks in terms of performance and risk-taking. In fact, the latest legislative activity that exerted a significant impact on the operation of banks was the Sarbanes-Oxley (SOX) Act, which was enacted in mid-2002 with the purpose

[4] With the implementation of the Dodd-Frank Act and the establishment of the Office of Thrift Supervision in July 2011, all thrifts were required to file and submit a Call Report from March 2012.

to set new or enhanced disclosure standards for all public company boards including those of banking firms. Along the same lines, by using a data period that ends in 2009q4, we do not have to account for the Dodd-Frank Wall Street Reform and Consumer Protection Act Regulatory Act (commonly referred to as Dodd-Frank Act), which signed into law in July 2010 and transformed the entire banking landscape to a considerable extent.

3.2. Distressed banks

The group of distressed banks consists of the banking firms, which either filed for bankruptcy or were bailed out via TARP. We acknowledge that 'distress' and 'failure' are two separate concepts and that failure as well as bailout can be included in the broader category of distress. Whether a failure, or a bailout it is the regulatory decision to resolve a distressed institution that we consider in our analysis. In other words, both failures and bailouts represent a regulatory action. Under the latter action a distressed bank remains alive as a going concern entity, whereas under the former action the bank loses its charter.

In classifying failed and bailed out banks as distressed institutions, we rely on the formal definitions assigned to distress and failure in several early warning studies. As shown below, the literature clearly considers bailouts as one of the key resolution mechanisms in case of distress. That said, we follow the intuition found in Wheelock and Wilson (2000) and Brown and Dinc (2011) according to which the bailout of a distressed bank might prevent a failure as well as that in De Young et al. (2009) who argue that without the bailout a bank might have become insolvent. In fact, this intuition is confirmed in the context of our analysis by the fact that, as of October 31, 2016, 32 bailed out banks were in bankruptcy/receivership, and 4 were either merged or acquired.[5] In addition, more than 100 banks are still not in a position to fully repay TARP money,[6] and many others are either reluctant to exit TARP, or lie behind on their dividend and interest payments raising serious doubts about their soundness (see Wilson, 2013; Croci et al., 2016; Calabrese et al., 2017).

According to Arena (2008), the following three categories are involved in the broader concept of failure: a) bank recapitalisation or liquidity injection, b) suspension of the bank's operations, and c) bank closure by regulators. In a similar vein, De Young et al. (2009) define a failed bank

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[5] Source: https://www.treasury.gov/initiatives/financial-stability/TARP-Programs/bank-investment-programs/cap/Pages/payments.aspx

[6] Source: https://projects.propublica.org/bailout/list/simple

either as a bank that goes bankrupt, or as one that receives regulatory assistance (e.g., a capital injection). Gonzalez-Hermosillo et al. (1997) also refer to the occurrence of bank intervention in the form of financial assistance, such as recapitalisation, to define failure broadly. The definition of distress in Poghosyan and Cihak (2011) relies on one of the following keywords: rescue, bailout, financial support, liquidity support, government guarantee, and distressed merger. The study of Mare (2015) defines a bank in default as one entering into special administration (i.e., conservatorship) under which the distressed bank remains alive as a going-concern entity, or compulsory liquidation which is a gone-concern action. Further, Mare states on p.34 that "distress may be resolved through a private solution (i.e., merger and acquisition), take over, bail out, or closure of the failing bank." Calabrese et al. (2015) consider a failed bank as being bankrupt, dissolved, or in liquidation, while Calabrese et al. (2017) consider the financial assistance given to a bank by regulators as a distress event even though the institution remains open and its charter survives the resolution process.

We do not consider any banks in our analysis which have been merged with or acquired by another financial institution. The reason is that, even though mergers and acquisitions might be due to strategic reasons like, e.g., the creation of scale and scope economies under normal economic conditions, in the case of financial debacle, the majority of consolidated institutions are on the verge of distress and are seen as not being able to survive on their own. This echoes Wheelock and Wilson (2000)'s finding that the closer to insolvency a bank is, the more likely is its merger or acquisition. In the same vein, Arena (2008) provides evidence that the merged and acquired banks share very similar characteristics with failed banks. Moreover, Poghosyan and Cihak (2011) define distressed mergers as forced mergers with healthier banks, while Mare (2015) treat mergers as a resolution mechanism of troubled banks. In this context, the studies of Lanine and Vennet (2006), Lu and Whidbee (2013), Fiordelisi and Mare (2013), and Berger et al. (2016) exclude merged and acquired institutions from their empirical analyses. In line with the aforementioned studies, acquired banks as well as those which have been merged with some other institution during the crisis not at the initiative of the Federal regulatory agencies are considered to be a third group of distressed banks together with the failed and bailed out banks, which comprise the two key distressed banking groups under scrutiny in our study. As such, and in order to avoid any spurious effects on the examined probabilities of failure and bailout, these banks are excluded from our sample.

3.2.1. Failed banks

Failed banks are defined as the insured banks that were closed requiring disbursements by the FDIC from the onset of the crisis in mid-to-late 2007 through the end of our data period. In general, a bank is closed when regulatory authorities determine that it is critically undercapitalised and deem it unable to meet its obligations to depositors and to other creditors. In the event of failure, the institution's charter is terminated and some or all of the assets and liabilities are transferred to a successor charter. The FDIC acts as a receiver and is in charge of the failure resolution process.

There are mainly two failure resolution mechanisms: the 'purchase-and-assumption' and the 'deposit payoff'. Under the former mechanism, insured deposits are transferred to a successor bank, and the charter of the failed institution is closed. In most of the purchase-and-assumption transactions, additional liabilities (e.g., part or all of its uninsured deposits) are assumed by and some or all of its assets are transferred to the acquiring bank. FDIC usually provides assistance to the acquirer most often in the form of loan loss sharing agreements. In the case of remaining assets and liabilities, these are liquidated and the liquidation costs are internalised. The acquiring bank usually compensates FDIC for the franchise value from the failed bank's established customer relationships, which helps reduce the insurer's resolution cost. In a deposit payoff transaction, FDIC pays the failed bank's depositors the full amount of their insured deposits, the bank's charter is closed, and there is no successor institution. Typically, deposit payoffs are observed when no other bank is interested in assuming the assets and liabilities of the failed bank.

On 28 September 2007, NetBank was the first banking firm to fail in the U.S. in the recent crisis. FDIC took receivership of NetBank and all the insured deposit accounts were transferred to an assuming institution. Some days later, on 4 October 2007, Miami Valley Bank was also shut down by the authorities. The collapse of Miami Valley Bank was followed by those of Douglas National Bank and Hume Bank in early 2008. Importantly, the number of failures increased rapidly from 2008 onwards. In total, for the period starting from October 2007 (2007q4) and extending to the end of December 2009 (2009q4), there have been recorded 167 bankruptcies in the U.S. banking sector and the FDIC has been appointed receiver of all the failed institutions.[7] In all these 167 failures, the purchase and assumption resolution process was applied, implying that deposits, assets and other liabilities were transferred to a successor bank.[8]

3.2.2. Bailed out banks

To stabilise the economy and the financial system, the U.S. Congress established TARP on October 3, 2008 and authorised the U.S. Treasury to buy up to $700 billion in troubled assets like mortgage-backed securities. On October 14, a revision of TARP was announced: the Treasury was authorised to directly inject capital into the undercapitalised banks under the CPP - the key component of TARP- by purchasing non-voting senior preferred shares and equity warrants. Those injections were intended to support the participated banks through the expansion of their capital base and provide stability to the system. More formally, the programme was "…launched to stabilise the financial system by providing capital to viable financial institutions of all sizes throughout the nation."[9] Therefore, based on its definition *per se*, TARP was a bailout programme that focused on banks of all sizes and not just on large and complex financial institutions. Qualified institutions included bank and financial holding companies, savings and loan holding companies, and insured depository institutions, which were established and operating in the U.S., and were not controlled by a foreign bank.

On October 20, 2008, the Treasury issued the viability criteria for the federal banking agencies to apply in the review of CPP applications. The criteria were based on the applicant bank's examination ratings and selected performance ratios without considering potential funds received under CPP; however, the Treasury has never issued the viability criteria publicly. After reviewing an application, the agency was required to submit the application and its recommendation to the Treasury. Based on the recommendation from the agencies, the Treasury made the final decision on whether or not to implement the capital purchase.

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[7] The relevant data has been collected from the official FDIC web site. The names of the banks, their distribution across the U.S. states and cities, the date that every failed institution ceased to exist as a going concern entity, the estimated assets and deposits of each institution at the time of failure, and the cost of every individual failure for FDIC are all available upon request.

[8] To give the broad picture of the extent of bank failures in the recent crisis, we indicate that only 30 banking institutions went bankrupt in the U.S. from 2000 through the beginning of the crisis.

[9] For an overview of CPP as described in the official page of the U.S. Department of Treasury, see: https://www.treasury.gov/initiatives/financial-stability/TARP-Programs/bank-investment-programs/cap/Pages/default.aspx

The investment in preferred stock was determined by the Treasury and ranged from 1% to 3% of a bank's risk-weighted assets with an imposed cap of $25 billion. In return for the capital infusion, TARP recipients subjected to: a) restrictions on their senior executive compensation plans and practices, b) a three-year period during which they were not allowed to repay TARP funds, c) a requirement to pay a dividend rate of 5% per year to the Treasury for the first five years and 9% afterwards as long as the securities were outstanding, d) a requirement to pay a 7.7% interest rate on debt instruments that was set to increase to 13.8% after five years. In February 2009, the American Recovery and Reinvestment Act revised the TARP rules, eliminating the three-year period and imposing stricter restrictions on total annual compensation for senior executives at recipient banks in order to incentivise banks to repay or redeem the preferred stock at an earlier time.

TARP was composed of two key phases.[10] In the first phase, nine of the largest U.S. financial institutions were arm twisted by authorities to participate in the programme. Indeed, on the same date that the Treasury launched CPP, the nine banks, which together accounted for approximately 55% of U.S. banks' assets, announced that they would subscribe to the facility in a total amount of $125 billion. Those nine institutions were Bank of America, Citigroup, JP Morgan Chase, Wells Fargo, Morgan Stanley, Goldman Sachs, Bank of New York Mellon, State Street, and Merrill Lynch. In the second phase of TARP, all qualified financial institutions were eligible to apply for financial assistance. Accordingly, participation in the first phase of the programme was rather mandatory, whereas, in the second phase, banks were not forced but chose to issue preferred stock after having voluntarily applied and being approved for issuance.

To construct the sample of bailed out banks, we refer to the complete list of TARP recipients (i.e., both voluntary and involuntary recipients) as obtained from the U.S. Treasury. This list discloses all the financial institutions that received TARP funds via CPP together with the respective transaction dates and investment amounts.[11] We trace all banks which participated in the programme either directly, or through their parent holding companies (HCs, henceforth). In total, we identify 736 TARP investment transactions excluding any multiple transactions, i.e., transactions in which a bank is involved in more than once. Out of these 736 institutions that received capital injections, 47 were thrifts which, as earlier mentioned, are excluded from our

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[10] See Calomiris and Kahn (2015) for an analysis of the TARP phases.

[11] See: https://www.treasury.gov/initiatives/financial-stability/reports/Pages/TARP-Investment-Program-Transaction-Reports.aspx

analysis. This leaves 689 institutions in our sample, out of which 596 are HCs and 93 are commercial and savings banks. We follow Li (2013) and Croci et al. (2016) in making the realistic assumption that if a HC was approved to participate in TARP, its subsidiary banks would have received some fraction of TARP funds. Out of 596 HCs that participated in TARP, 56 were multi-HCs, while the remaining 540 were mono-HCs. We match all HCs to their subsidiary banks by hand-matching the relevant information found in the Consolidated Financial Statements for Bank and Financial Holding Company Report (FR Y9-C Report) to the 'higher-holder' codes of the examined banks found in Call Reports. In doing so, we obtain a total of 731 banks that received TARP funds via their parent HCs. We add to this figure the 93 commercial and savings banks which are not linked to some HC to construct the final sample of 824 banks that received TARP support.[12]

3.3. Non-distressed banks

As already discussed, a bank either files for bankruptcy, or receives financial assistance via TARP. If neither of these two events occurs, and also if a bank is neither merged nor acquired, then the bank survives the crisis and remains in the sample up to the very last quarter of the examined data period. The banks falling into this category are labelled 'non-distressed'.

3.4. Sample banks

We begin with a total number of 8,722 active commercial and savings banking institutions that filed a Call Report in 2003q1. Since our model relies on the competing distress events of failure and bailout, and since bailouts end in 2009q4, we cannot consider any failures from 2010q1 onwards in our analysis because one of the two competing events, that of bailout, cease to exist. On the other hand, if we incorporate the banks that failed in 2010q1 and thereafter in our sample, then these banks will appear in our empirical analysis as being non-distressed since they failed at a point later than the end of our sample period. Therefore, we decide to exclude the banks that failed after the observation period, i.e., from 2010q1 to 2015q4, in order to avoid any sort of estimation bias in our model. We also exclude all the banks that were merged with or acquired by some other institution through a market deal. By checking the data for reporting errors and

[12] The detailed list of these banks is available upon request.

other relevant inconsistencies, we end up with an unbalanced data set of 7,602 banks of which 167 are bankrupt institutions, 824 are bailed out, and 6,611 are non-distressed.

3.5. A dynamic competing risks hazard model à la Shumway

In the context of our analysis, a bank drops from the sample either through a failure or a bailout. These two distress events are considered as being competing events, which introduce competing risks or, alternatively, competing hazards. We, therefore, resort to a competing risks hazard model that entails no inference methods other than those used in the traditional hazard analysis.

Our model examines the joint determination of the probability of a bank to fail or to be bailed out and relies upon a set of bank-specific and environmental time-varying covariates à la Shumway (2001). In contrast to standard discrete choice models like discriminant analysis and traditional probit and logit models, which have been extensively employed in the relevant literature as described in Section 2, the dynamic hazard model of Shumway is capable of incorporating information about the time which remains before an incident of distress occurs. As such, it can be estimated using the entire life span of information for each sample banking company. Consequently, its dynamic nature provides us with the advantage of examining how the probability of a bank becoming distressed may vary over time.

An additional deficiency in the applications of static prediction models is that they cannot accommodate the temporal concept of distress as they require the relevant process to be fairly stable. Being based on a dichotomous classification of distress vs non-distress which treats all the decision units that belong to the same group in the same manner, static models disregard the timing of distress in that they do not examine whether distress falls within a particular time window or not. That is, the distress process (either resulting in a failure or in a bailout in the context of our analysis) is assumed to be stable over a considerable period of time for a static model specification to be run. By contrast, the time dimension of distress is incorporated into our dynamic empirical approach.

Researchers who resort to static models to predict financial distress must decide when to observe their sample bank's operating characteristics. In most cases, they choose to collect year-end data for one or two years before bankruptcy (see, e.g., Lane et al., 1986; Kolari et al., 2002). Therefore, static models can only consider one or maybe two sets of explanatory variables in terms of time for each sample entity. By arbitrarily choosing when to observe the bank characteristics, forecasters who use static models introduce a sort of selection bias into their estimates. In addition, the characteristics of banks change over time and these changes cannot be captured in a static empirical context. Ignoring the time-related behaviour and performance of banks by following a single-period classification approach based on multi-period data sets, implies that static models are likely to produce distress probabilities which are biased and inconsistent estimates of the probabilities they approximate. As a consequence, test statistics that are based on static models may produce incorrect inferences.

For the aforementioned reasons, the forecasting power of our Shumway-type competing risks hazard model is expected to be generally higher than that of its static counterparts. Notwithstanding its attracting features, the Shumway model has been rather neglected by the early warning banking literature. To the contrary, the model is employed in the prediction of corporate bankruptcy providing highly accurate parameter estimates (see Chava and Jarrow, 2004; Beaver et al., 2005; Bharath and Shumway, 2008; Campbell et al., 2008; Bonfim, 2009).

Failed and bailed out banks drop out from our sample the quarter that follows the date they went bankrupt or received financial assistance, respectively. If, for instance, a bank failed or received TARP funds on 26 February 2009, then this bank is dropped out in 2009q2. For the failed institutions, the reason for this is straightforward: balance sheet data are no longer available for a banking firm once it goes bankrupt. As regards the bailed out banks, the rationale is twofold: first, once a bank is being bailed out, it can no longer be known whether or when that bank would fail at some later point in time as discussed in Section 3.2; second, the money assistance that a bank receives constitutes an exogenous intervention in the bank's operation which has an effect on its overall performance. In specific, the performance of a bailed out bank is, *ceteris paribus*, expected to improve over time due to the external funding received and not due to other factors which are endogenously linked to its performance like, for instance, the prudent and efficient management of the bank.

We define the following event-specific hazard function of survival time *T*:

$$h_j(t;x) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t,\ J = j \,\middle|\, T \geq t, x)}{\Delta t}, \tag{1}$$

where $h_j(t; x)$is the instantaneous rate of bank exit from the sample due to distress event *j* at time *t* given *x* in the presence of *j*-1 events, *x* is the vector of bank-specific and environmental covariates, and *J* is the type of distress event with *j*=1, 2, where 1 stands for failure and 2 for bailout. Equation (1) is the limit of the probability that a bank is dropped due to event *j* in a very small time interval $(t, t + \Delta t)$, given that the bank has survived to time *t*. As previously mentioned, our sample contains quarterly accounting data over the period 2003q1-2009q4, implying that *t* stands for quarters and takes values on the closed interval [1,2,…28], where *t*=1 corresponds to the first quarter of 2003 (2003q1), and *t*=28 corresponds to the last quarter of 2009 (2009q4). Since our independent variables are observed at quarterly intervals, we treat each quarter as a life-at-risk interval.

As already noted, the occurrence of either distress event in any given instant precludes the other in the sense that no sample bank that received financial assistance via TARP did later fail. This is to say that the bailout of a bank precludes its failure and *vice versa*, implying that the two distress events are mutually excluded. Hence, the overall hazard is given by the sum of the two type-specific hazards:

$$h(t; x) = \sum_{j=1}^{2} h_j(t; x). \tag{2}$$

We can now define the survival function, which shows the probability that a sample bank survives longer than *t*:

$$S_j(t; x) = P[T > t; x] = \exp\left[-\int_0^t h_j(u; x) du\right]. \tag{3}$$

The probability density function is given by:

$$f_j(t; x) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t,\ J = j \,|\, T \geq t, x)}{\Delta t} = h_j(t; x) S_j(t; x). \tag{4}$$

Bank failures and bailouts occur at discrete points in time t_{ij}, where i=1, 2,…, n (n=7,602) indexes the sample banks. We construct a dummy indicator denoted by d_{ij} which equals to unity if the bank i exits the sample at some point in time t_{ij} due to any of the examined distress events and zero if it survives up to end of the data period. If j_i stands for the distress type of bank i, then we can define the partial likelihood function as follows:

$$L = \prod_{j=1}^{2} \prod_{i=1}^{n} ((h_{j_i}(t_{ij}; x_{ij}))^{d_{ij}} \; S(t_{ij}; x_{ij})). \tag{5}$$

We note that j_i does not enter into Equation (5) if d_{ij} is equal to 0; that is, d_{ij} is the censoring term. Hence, our model assumes a censored observation for each competing distress event. Put differently, competing hazards are treated as censored to one another: in modelling the failure hazard, bailed out banks are treated as censored observations at the date of bailout. Similarly, in modelling the bailout hazard, banks that fail are treated as censored observations at their failure date.

We have made no functional assumptions to obtain Equation (1). Since time is continuous and the failure and bailout hazards remain constant over discrete time intervals (i.e., from one quarter to another), then the piecewise exponential approach is preferable:

$$h_j(t; x) = h_{0j}(t) \exp(\beta_j' x), \tag{6}$$

where $h_{0j}(t)$ reflects the underlying or baseline hazard function that shows how risk changes over time; β_j' is the coefficient vector that indicates the effects of covariates for the event type j. It can be shown that β_j' is not the same for all j, meaning that different sets of coefficients are jointly estimated for different types of distress in each regression. This is in line with the specification of the baseline hazard function $h_{0j}(t)$ in Equation (6), which is indexed by j and, as such, is allowed to differ between the different distress types.

Following Shumway, Equation (6) can be generalised to incorporate time-varying covariates as follows:

$$h_j(t; x(t)) = h_{0j}(t) \exp[\beta_j' x(t)]. \tag{7}$$

In Equation (7), the failure and bailout hazards are assumed to be independent from each other. In reality, however, the two hazards are both directly and strongly related to the decisions of regulatory authorities and, hence, to one another. More specifically, a banking institution in distress either receives TARP assistance, or it is left to go bankrupt. Not only may a bank be more likely to be bailed out if it is in distress, but the regulators' decision to approve or reject a TARP application is also linked to the individual health of the applicant bank. We, therefore, introduce a heterogeneity term denoted by v_j in Equation (7) and obtain the following formula:

$$h_j(t; x(t)) = h_{0j}(t) \exp[\beta_j' x(t) + v_j]. \tag{8}$$

Equation (8) allows dependence between the two types of bank exit from the sample, as it does not require v_j and v_l to be independent for $j \neq l$, where l = 1, 2. We therefore allow the banks which are more likely to receive financial assistance for reasons which are not captured by our model specification to be more -or less- likely to be closed by regulators.

3.6. The model covariates

In this section, we describe the set of covariates x that we employ in our model. The underlying patterns of distress are analysed based upon a broad scope of observable and non-observable factors: the components of the CAMELS regulatory ratings system, a set of bank-specific indicators of systemic importance, a group of additional key bank-specific factors, and a set of control variables related to macroeconomic and financial conditions. The balance sheet and income statement variables are of quarterly frequency and are collected from Call Reports as found in the website of the Federal Reserve Bank of Chicago and that of the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution. Interest rates and yields are collected from the Federal Reserve Board and the U.S. Department of Treasury and are also of quarterly frequency. All variables and the relevant data sources are summarised in Appendix A.

3.6.1. CAMELS components

The CAMELS rating system, which has been utilised by U.S. authorities for more than two decades now to monitor the safety and soundness of individual banks, consists of the following six components: Capital adequacy, Asset quality, Management expertise, Earnings strength, Liquidity, and Sensitivity to market risk. We follow the relevant literature (see, e.g., Stojanovic et al., 2008; Duchin and Sosyura, 2012) to construct a vector of bank performance and risk-taking measures that largely resembles the original CAMELS components. We use the standard equity-to-assets ratio as an indicator of bank capital strength (*CAP1*); asset quality is measured by the ratio of non-performing loans to total loans and leases (*ASSETQLT1*); management expertise is measured by managerial efficiency as calculated by the input-oriented Data Envelopment Analysis model (*MNGEXP1*);[13] the return on assets is applied as a measure of earnings strength (*EARN1*) and is expressed as the ratio of total net income (given by the difference between total interest plus non-interest income and total interest plus non-interest expense) to total assets; the ratio of cash and balances due from depository institutions to total deposits reflects the degree of bank liquidity (*LQDT1*); and, the sensitivity to market risk (*SENSRISK1*) is proxied by the change in the slope of the yield curve (given by the change in the quarterly difference between the 10-year U.S. T-bill rate and the 3-month U.S. T-bill rate) divided by total earning assets.

3.6.2. Indicators of systemic importance

We account for four indicators of systemic importance. We first incorporate bank size (*SIZE*) measured by the natural logarithm of the book value of total assets. Further, we adopt three metrics of bank complexity. We measure organisational complexity (*ORGCOMPL*) by the log of the product of the number of branches that each sample bank has and the number of U.S. states in which the bank has branches, because banks which are more decentralised with a greater number of branches are characterised by more complex organisational structures (see Berger and Bouwman, 2013; Berger and Roman, 2015). We also use two measures of complexity, which capture the scope and diversity of bank business lines. Both measures rely upon the Bank for International Settlement methodology for the designation of globally systemically important banks that measures complexity using the notional value of Over-The-Counter (OTC)

[13] The calculation of *MNGEXP1* is fully described in Appendix B.

derivatives, the balance sheet presence of "Level 3" assets (i.e., assets for which prices cannot be inferred by either markets or models), and the size of the trading and available-for-sale securities (BCBS, 2014). The securitisation activity of the sample banks is captured by the outstanding principal balance of loans, leases, and all relevant assets securitised and sold to other financial institutions with recourse or other credit enhancements divided by total assets (*SECASSET*). We also measure the exposure of banks to financial derivatives using the ratio of the total amount of outstanding derivative contracts to total equity capital (*DERIV*). The numerator of *DERIV* includes the interest rate, foreign exchange, equity, commodity and other derivative contracts that are held either for trading or hedging purposes.

In the years running up to the crisis, commercial banks diversified away from the traditional intermediation services of deposit-taking and loan-granting into market-based products like securitised assets and financial derivatives. The observed growth in this sort of products which mainly generate non-interest income and are commonly not reported on banks' balance sheets has been widely recognised in the literature as considerably altering the risk profile of banks (De Jonghe, 2010; Brunnermeier et al., 2012; Fahlenbrach et al., 2012; Acharya et al., 2013; Battaglia and Gallo, 2013). Literature has also documented the relevance of such activities in bank performance (e.g., Rogers and Sinkey, 1999; Casu and Girardone, 2005) and in the probability of failure (see, among others, Lepetit et al., 2008; DeYoung and Torna, 2013; Van Oordt, 2014). Even though securitised products and financial derivatives have had a quiet few years (mostly from 2008 to 2011), a resurgence of these and other relevant trading activities has been lately observed (Boot and Ratnovski, 2016; Le et al., 2016; Buchanan, 2017). It is therefore crucial to investigate the effects of this type of business on the likelihood of a bank to fail or to need financial assistance in the context of our early warning system.

3.6.3. Additional key bank-specific variables

The TARP literature has demonstrated that connections with regulators and policy-makers have a considerable impact on the decision of authorities to save a bank through the extension of a TARP facility. We use a group of variables to capture these connections. First, we follow Blau et al. (2013) and resort to the Center for Responsive Politics (CRP)'s Revolving Door database to construct an indicator variable (*POLCON*) to proxy the connections that our sample banks have with policy-makers. *POLCON* is equal to unity if a sample bank has employed, or is currently employing an individual who is also employed or has been employed in the federal government or appointed to a government advisory board, a congressional or presidential cabinet entity, or an independent commission. Second, we identify any connections that banks may have with regulatory and supervisory authorities. We follow Bayazitova and Shivdasani (2012), Duchin and Sosyura (2012), Li (2013), and Berger and Roman (2015) to construct an indicator variable (*FEDCON*) that is equal to unity if an executive at a sample bank was on the board of directors of one of the 12 Federal Reserve Banks or one of their branches either in 2008 or 2009. We first obtain the relevant data on the top executives of our sample HCs from BoardEx and then match them to the list of directors from the Fed's website. Third, we use House of Representatives Committee data and follow Berger and Roman (2015) and Duchin and Sosyura (2014) to construct a dummy variable (*COMMIT*) that equals one if a sample bank is headquartered in a district of a House member who served on the key finance committees involved in drafting and amending TARP, i.e. the Subcommittee on Financial Institutions, or the Subcommittee on Capital Markets of the House Financial Services Committee, either in 2008 or 2009. We resort to data from the U.S. Census Bureau and the U.S. Library of Congress to match the sample banks with the relevant congressional districts using the zip codes of their headquarters. And, forth, as an additional measure of the ties that may exist between the financial services industry and politicians, we refer to the contributions of banks to federal political campaigns (*CAMP*). We collect data from the Federal Election Commission that cover contributions from Political Action Committees (PACs) to candidates' election campaigns. Following Duchin and Sosyura (2012) and Bayazitova and Shivdasani (2012), *CAMP* takes the value of one if a bank has made PAC contributions in the election cycle for the 2008 congressional election to the members of the Subcommittee on Financial Institutions or those of the Subcommittee on Capital Markets.

A number of bailed out banks played the role of acquirers in the merger and acquisition (M&A) deals that took place during the examined period but, mainly, after the outbreak of the crisis. We, therefore, resort to the relevant files of the Federal Reserve Bank of Chicago to investigate whether a bank has been involved in a M&A transaction as acquirer.[14] We introduce a dummy variable (*MA*), which is equal to unity when the acquirer bank *i* is involved in a M&A transaction and remains equal to one until the end of the data period. For example, if an acquisition occurred on April 15 2008 then this transaction is recorded in the second quarter of

[14] The relevant data are found in: https://www.chicagofed.org/banking/financial-institution-reports/merger-data

2008, meaning that *MA* takes the value of one in 2008q2 and remains as such for all the subsequent quarters.

Further, we introduce a dummy indicator (*MSA*) to account for regional disparities that may have an impact on the failure/bailout probabilities. *MSA* is equal to one if a bank is located in a Metropolitan Statistical Area -i.e., an integrated economic and social unit with a recognised large population nucleus- and zero otherwise. The geographical location of each sample bank is identified through Call Reports; detailed data for Metropolitan Statistical Areas are taken from the U.S. Office of Management and Budget.

It is well-documented in the banking literature (see, e.g., DeYoung, 2003) that the behaviour and performance of the newly chartered banks substantially differ from those of banks in operation over a rather long period of time. More specifically, once a bank first enters the market, its financial performance tends to lag by a considerable margin compared to that of the existing banking firms. That said, we account for the so-called *de novo* banks, defined as banks less than five years old by including the relevant dummy (*DENOVO*) in our model.

We also construct an indicator variable (*PUBLIC*) that shows if a bank is listed on the stock exchange market. Since the decision-making units we examine are not holding companies, the subsidiaries of publicly traded HCs are considered to be public. Banks with private placements of shares with a Committee on Uniform Securities Identification Procedures (CUSIP) number, banks without a stock exchange listing, and banks whose HC is not listed on the stock exchange are treated as non-public. The data on trading and listing are derived from the Center for Research in Security Prices (CRSP) database. A dummy variable (*HC*) showing whether a sample bank is a subsidiary of a HC is also considered in our empirical analysis.

3.6.4. Macroeconomic and financial variables

After the outbreak of the crisis, the ability of banks to lend to each other via the interbank market or to borrow from money markets was considerably reduced. This gave birth to liquidity shortages, which occur when a bank is unable to meet its current obligations as they come due. In efforts to bolster banks that were constrained in obtaining new funds and to boost cash flow in the market through the support of credit supply with the utmost purpose to avoid a more severe credit crunch and to help ease the crisis, the Fed -like the European Central Bank, Bank of England, and Bank of Japan- implemented several rounds of quantitative easing programmes mainly through the purchase of Treasury securities. We, therefore, introduce a dummy variable (*QE*) to capture the first quantitative easing round in the U.S., which extended from November 2008 to June 2010. *QE* takes the value of 1 in 2008q4 and remains unchanged until the end of our sample period to indicate that a quantitative easing program was in place in each and every of the subsequent quarters.

Authorities may find it optimal in terms of economic and social costs to bail out a bank which is in distress instead of closing the bank if there are too many distressed banks in the economy. This is to say, regulators may become reluctant to let a bank fail once a crisis is considered to be of systemic nature. Following Brown and Dinc (2011), we account for the Too-Many-To-Fail effect in bank regulation using a measure of the relative bank capital soundness denoted by *TMTF*. This is obtained as the average capital ratio (total equity capital to total assets) of other banks in the economy weighted by bank total assets.

It is widely accepted that economic performance has a considerable impact on demand and supply of banking services. More precisely, high levels of banking activity are generally related to favourable economic conditions like price stability and economic development. In this context, the macroeconomic environment is largely considered to have an effect on the performance and the risk-taking of banks. We thus employ the quarterly change in the U.S. Consumer Price Index (*INF*) to control for fluctuations in the level of prices, and the GDP output gap (*GDP*) to control for variations in economic growth.

3.7. Summary statistics

3.7.1. CAMELS and systemic indicators

In Table 1, we present and discuss the summary statistics on CAMELS components (*CAP1*, *ASSETQLT1*, *MNGEXP1*, *EARN1*, *LQDT1*, and *SENSRISK1*), and systemic indicators (*SIZE*, *ORGCOMPL*, *SECASSET*, and *DERIV*) for the three groups of banks. Further, we make pairwise comparisons of the performance, financial soundness and the systemic importance among the three groups by conducting a univariate analysis on the mean differences of the aforementioned variables. We rely on average quarterly data over the pre-crisis period, i.e., from 2003q1 to 2007q3. The fourth quarter of 2007 (2007q4) is considered to be the starting point of the crisis for two main reasons: first, bank failures begun to unravel in the very beginning of that quarter; and, second, that was the time when the TED spread (the difference between the yield on the three-month London Interbank Offered Rate -LIBOR- and the yield on three-month U.S. T-bills) which is one of the most widely-used indicators of credit risk, widened to almost 200 basis points relative to a historically stable range of 10-50 basis points.

[INSERT TABLE 1 HERE]

We notice that non-distressed banks were on average well-capitalised in the years preceding the crisis with a mean equity capital ratio (*CAP1*) of 12.63%. The mean value for the capital ratio of failed banks was equal to 10.17%, while that of bailed out banks was 9.23%, showing that the latter group experienced a relatively lower capital adequacy compared to its peers prior to the crisis. The reported mean differences are all statistically significant at the 1% level. Turning to examine the asset quality indicator (*ASSETQLT1*), figures reveal that the asset portfolio of non-distressed banks was the least risky compared to the relevant portfolios of the other two groups. In specific, the mean of *ASSETQLT1* was equal to 0.58% for non-distressed banks, 1.40% for failed banks, and 1.92% for bailed out banks. Therefore, failed banks experienced a better asset quality if compared to that of bailed out banks as they had 0.52% less non-performing loans compared to the assisted institutions. The pairwise differences in means for *ASSETQLT1* are all significant at the 1% level. Moreover, non-distressed banks shared very similar managerial efficiency scores (*MNGEXP1*) with failed banks (0.79 and 0.77, respectively); the reported difference of 0.02 points is found not to be statistically significant. On the other hand, the management of bailed out banks is found to be less efficient by 0.15 points and 0.13 points than that of non-distressed and failed banks, respectively; the reported mean differences are statistically significant at the 5% level. Focusing on *EARN1*, we observe that bailed out banks were the least profitable banks amongst the examined institutions prior to the outbreak of the crisis: they earned 0.67% less than non-distressed banks and 0.13% less than failed banks. Both mean differences are significant at the 1%. Further, the profitability of failed banks was significantly lower if compared to that of non-distressed banks. In specific, failed banks earned 0.54% less than non-distressed banks. As regards the mean liquidity ratio (*LQDT1*), this was equal to 4.74% for non-distressed banks, 3.01% for failed banks, and 2.01% for bailed out banks. That is, failed banks held fewer liquid assets than non-distressed banks, while bailed out banks held the most illiquid portfolio of assets amongst their peers. The corresponding mean differences are all significant at the 1% level. To continue, non-distressed banks were, on average, almost equally sensitive to market risk with failed institutions with an average *SENSRISK1* of 10.77% and 10.68%, respectively. The reported mean difference of 0.09% is not found to be statistically significant. On the other hand, the average sensitivity of bailed out banks to market risk was equal to 17.18%, revealing that this group of banks was highly exposed to market-based activities. The relevant mean differences (-6.41% and -6.50%) are significant at the 5%.

Importantly, non-distressed banks had almost the same average size (*SIZE*) with the failed institutions: $0.86 billion and $0.89 billion, respectively. The mean difference of $0.03 billion is not statistically significant. Bailed out banks, on the other hand, had a size of $9.98 billion, being, on average, more than 11 times larger compared to either the non-distressed or the failed banks. The relevant differences in the means of *SIZE* are found to be highly significant. As regards the organisational complexity (*ORGCOMPL*) of the three groups of banks, bailed out banks are found to be the most complex ones (1.64), whereas non-distressed banks are the least complex institutions (1.19). Notably, the level of organisational complexity of failed banks (1.40), even though it is lower by 0.24 compared to that of bailed out banks, it is not substantially different from a statistical viewpoint. Turning to the business model complexity, the banks that went bankrupt are found to have been engaged in securitisation activities to an almost equal degree with non-distressed banks in the years preceding the crisis. More concretely, the mean proportion of *SECASSET* is equal to 10.23% for non-distressed banks. This percentage is only 0.34% higher compared to that of failed banks (9.89%) and the reported difference is not statistically significant. To the contrary, the asset securitisation business of bailed out banks is heavier compared to that of non-distressed and failed institutions with a mean value which equals to 17.32%. The mean differences of -7.09% and -7.43% with non-distressed and failed banks respectively are both statistically significant at the 1% level. If we now turn to examine the exposure of the three banking groups to derivative products (*DERIV*), the picture we obtain is very similar to that obtained for securitisation activities. In specific, we do not document any significant differences -either from a numerical or a statistical viewpoint- in the involvement of either the non-distressed or the failed banks with derivative activities. On the other hand, the mean value of *DERIV* for the assisted institutions equals to 21.63%, which is 13.49% and 13.70% higher than the relevant means for the groups of non-distressed and failed banks, respectively. The reported mean differences are both highly statistically significant.

Taken together, the performance, size, and business complexity of bailed out banks were all significantly different from those of their peers during the pre-crisis period: they were much larger institutions, which experienced lower capital ratios, riskier portfolios of assets, weaker managerial efficiency, lower profitability, increased illiquid assets, higher degree of sensitivity to market risk, and considerably heavier exposure to non-traditional banking business. On the other hand, the banks that went down during the crisis, even though they performed worse than those that remained afloat in terms of capital adequacy, asset quality, profitability, and liquidity, had almost the same size with their non-distressed peers and also shared some common features with them like management quality, the level of sensitivity to market risk, and the degree of engagement with non-traditional products. As regards organisational complexity, bailed out banks demonstrated a more complex structure compared to that of the non-distressed banks, but not so highly different structure from a statistical perspective compared to that of failed institutions.

3.7.2. Additional bank-specific variables

Table 2 presents the summary statistics for the additional bank-specific variables we employ in our analysis. Several substantial and statistically significant differences between failed and bailed out banks are reported. We find that *POLCON* is significantly larger at the 1% level for banks that received TARP money than those that closed by regulators. Specifically, 7.38% of bailed out institutions have employed, or are currently employing at least one individual, who is affiliated or has been affiliated with the federal government or some other cabinet entity; the relevant percentage for the failed banks is only 1.70%. Similarly, if we turn to examine *FEDCON*, we observe that TARP banks are more closely linked to Fed regulators and supervisors compared to their failed peers (6.31% and 1.81%, respectively). The difference in the means is found to be statistically significant at the 1% level. Further, 9.36% of the TARP banks and 2.94% of the failed banks are headquartered in a district of a House member who served on the key finance committees (*COMMIT*); the reported difference is significant at the 5% level. Regarding the contributions of the two groups of banks to federal political campaigns (*CAMP*), 5.42% of TARP banks and 1.35% of the failed banks made such contributions and the relevant difference is highly significant.

An average of 27.24% of bailed out banks has been involved in at least one M&A transaction as acquirer during the sample period, whereas the relevant percentage of failed banks is only 2.80%. The difference in the means of *MA* for the two groups of banks is significant at the 1% level. To continue, 41.93% of the failed banks are located in a Metropolitan Statistical Area (*MSA*). The relevant percentage for banks that were bailed out is significantly higher at the 5% level and is equal to 71.41%. An additional considerable difference of failed banks compared to bailed out banks is that more than twice of the former group of banks are newly-chartered banks (*DENOVO*) compared to the latter group (8.07% vs. 3.20%, respectively), and that the reported difference in means is significant at the 1% level. Moreover, the summary statistics for *PUBLIC* show that the percentage of listed failed banks is equal to 2.78%, whereas that of listed bailed out banks is 7.56%; the reported mean difference is significant at the 1% level. Lastly, 10.62% of the failed banks are, on average, affiliated with a holding company (*HC*). The corresponding percentage for the assisted institutions is much higher and equals to 62.68%; the reported difference in the relevant means is significant at the 5% level.

[INSERT TABLE 2 HERE]

3.8 Bank distress

In Section 3.7, we showed that the average performance of failed and bailed out banks based on CAMELS components is relatively worse compared to that of non-distressed banks over the pre-crisis years. We now move a step further in our analysis and measure the level of distress of our sample banks using Z-score as a proxy for distress. Z-score is calculated as follows:

Let distress occurs when the total equity capital (*TE*) of a sample bank is smaller than its losses, where $-\pi$ stands for negative profits:

$$TE < -\pi \tag{9}$$

Then, the bank's probability of distress can be written in the following way:

$$p(TE < -\pi) = p(\pi < -TE) = p\left(\frac{\pi}{TA} < -\frac{TE}{TA}\right) = p(EARN1 < -CAP1) \tag{10}$$

where $p(\cdot)$ is a probability, *EARN1* and *CAP1* stand for earnings strength and capital adequacy as defined in Section 3.6.1, and *TA* stands for Total Assets. Suppose that $r = EARN1$ and $k = -CAP1$, where *r* and *k* are two random variables. We can then write eq. (10) as follows:

$$p(r < k) = \int_{-\infty}^{k} \psi(r)dr \tag{11}$$

where $\psi(r)$ is a density function. If *r* follows a normal distribution, we can rewrite the distress likelihood in terms of the standard normal density *Ψ(·)*:

$$p(r < k) = \int_{-\infty}^{z} \Psi(\zeta)d\zeta \tag{12}$$

where $\zeta = \frac{r-\rho}{\sigma}$ and $z = \frac{k-\rho}{\sigma}$ with ρ being the true mean and σ the standard deviation of *r*.[15] Z-score is the sample estimate of $-z$ (since z<0) and is defined in the following way for each sample bank and for each sample quarter:

$$Z_{it} = \frac{EARN1_{it} + CAP_{it}}{\sigma(EAPN1_{it})} \tag{13}$$

where *t* stands for quarters, *i* for the sample bank *i*, Z_{it} denotes Z-score for bank *i* at *t*, and $\sigma(EAPN1_{it})$ is the period standard deviation of *EARN1* which captures the volatility of bank *i*'s returns. Hence, *Z* combines profitability, capital risk, and return volatility in a single measure. Evidently, it is increasing in banks' average profitability and capital strength and decreasing in return variability. Overall, larger values of *Z* imply lower levels of distress.

We measure Z-score for each sample bank and for each quarter during the crisis period. We focus on this period because this is the time when all failures and bailouts occur. In the case of failed and bailed out banks, Z-score is measured for each quarter prior to the failure or bailout quarter, respectively. We then compute a summary (average) Z-score for each sample bank over

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[15] Normality is a rather strong assumption for the distribution of *r*. Nevertheless, because of Chebyshev's inequality, we know that regardless of the distribution of *r*, the upper bound to the distress probability is:

$$p(r \leq k) \leq \left(\frac{\sigma}{\rho - k}\right)^2 = \frac{1}{z^2}$$

the examined period and assign each Z-score to a decile. We sort all banks in deciles based on their summary Z-scores. The number of banks as well as the relevant percentage for each of the three banking groups by decile of distress is calculated and reported in Table 3. Banks in the top 10 percent (i.e., in Decile 1) achieve the highest Z-scores that reflect the lowest levels of distress; banks in the lowest 10 percent (i.e., in Decile 10) have the lowest Z-scores which show the highest distress levels.

[INSERT TABLE 3 HERE]

As expected, the great majority of the failed banks were in distress prior to their failure. In specific, the 68.26% of the banks that filed for bankruptcy during the crisis achieved the lowest Z-scores, while the 17.37% achieved the second lowest scores. Not surprisingly, the group of non-distressed banks confirms its soundness since only 2.07% and 1.44% are ranked in the lowest two deciles, respectively. The banks that received TARP funds, on the other hand, are found to be in distress: three out of four bailed out banks (75.85%) belong to the lowest two deciles, while only 5.71% belong to the top two deciles. The latter percentage possibly reflects that some non-distressed banks with lower capital ratios were at competitive disadvantage to raise equity due to market conditions, and, hence, have applied for a cheaper source of funding.[16] However, the great majority of bailed out banks is found to be in distress, which is consistent with the relevant findings and discussions in the TARP literature. For example, Bayazitova and Shivdasani (2012) document that banks that faced high financial distress costs obtained TARP equity infusions. Brei et al. (2013) suggest that recapitalisations can help sustain credit in the economy by helping banks to survive extreme distress and that TARP institutions were those facing serious financial distress. Li (2013) also describes TARP banks as being financially distressed, while Cornett et al. (2013) underlines the key TARP's goal of helping temporarily unhealthy banks get through a period of financial distress.

4. Regression results

4.1. In-sample estimation: Dynamic competing risks hazard model

We use non-distressed banks as the holdout banking group and estimate two different specifications of Equation (8): one specification that considers the CAMELS components and the indicators of systemic importance (columns 1a and 1b in Table 4), and a second one which

[16] We thank an anonymous reviewer for offering this insight.

also accounts for the additional bank-specific factors and the environmental variables (columns 2a and 2b in Table 4). The coefficients for the two types of distress are jointly estimated under both model specifications. A positive (negative) sign indicates an increase (decrease) in the failure/bailout likelihood given that the bank has survived up to that particular point in time.

[INSERT TABLE 4 HERE]

The results show robustness across the two model specifications: the signs of the estimated coefficients remain the same and the statistical significance levels of the coefficients are very similar (if not the same) across the two specifications. The impact of bank capital (*CAP1*) on failure and bailout probabilities is negative and statistically significant at the 1% level, indicating that banks with a stronger capital base are less likely to fail, and less likely to be bailed out. Put differently, banks which are highly levered are more likely to either go bankrupt, or to receive financial support by authorities given that they have stayed afloat up to the point in time that authorities will make the relevant decision. Higher credit risk as reflected in *ASSEQLT1* significantly increases the probability of a bank to fail; on the other hand, the impact of *ASSEQLT1*on the odds of bailout is not statistically significant. The expertise of bank managers (*MNGEXP1*) has a significantly negative effect at the 5% level on the hazard of failure, but no statistical impact on the bailout hazard. As expected, more profitable banks (*EARN1*) as well as those that hold a larger portion of liquid assets (*LQDT1*) in their portfolios have lower failure likelihood. The latter findings are significant at the 1% and 5% levels. Similarly, the relationship that holds between profitability and the level of liquidity with the bailout likelihood is negative and statistically significant at the 5% level. Lastly, sensitivity to market risk (*SENSRISK1*) is found to have a positive and statistically significant impact at the 5% level on both the failure and the bailout probabilities.

We can now turn to examine how the indicators of systemic importance influence the two probabilities under scrutiny. Bank size (*SIZE*) is found to be negatively linked to the failure probability, which implies that smaller banks are more likely to go bankrupt. Larger banks, on the other hand, have higher chances to receive financial assistance. Both effects are statistically significant at the 1% level across the two model specifications. These findings are in line with the main argument of Goodhart and Huang (2005) according to which it is optimal for authorities to rescue those banks whose size is above some threshold level. Importantly, our findings provide strong support to the Too-Big-To-Fail (TBTF) phenomenon: it is in the interest of bank managers to shape and follow strategies that focus on the size growth of their banks knowing that the bigger their bank becomes the more likely is to be bailed out and the less likely is to fail in the case of financial turbulence.

As regards the organisational complexity of banks (*ORGCOMPL*), this is negatively associated with the probability of failure and positively linked to the odds of bailout across the two model specifications. The estimated coefficients on *ORGCOMPL* are significant at either the 5% or the 10% levels. Hence, we can argue that the more complex the organisational structure of a bank is, the more likely is to receive TARP assistance and the less likely is to fail. This holds also true if the business model complexity is considered. The coefficients on both *SECASSET* and *DERIV* are found to be highly statistically significant, showing that securitised assets and derivative products can bestow substantial benefits on banks by allowing risks to be more precisely tailored to risk preferences and tolerances of banks and their customers. Both instruments increase the capacity of banks to price and bear risk and to allocate capital. In addition, the results imply that the combination of traditional banking products with modern activities transforms risks and reduces the odds of failure.

There are at least two channels through which product diversification leads to a reduction in bank riskiness. The first shows that non-interest income, which is produced by non-traditional financial instruments, is less sensitive to changes in the economic and business environment than interest income, which is produced by traditional products like real estate, commercial, industrial and other types of loans. Therefore, banks which rely more on the former type of income are typically exposed to less risk as they manage to reduce the cyclical variations in profits and revenues. Turning to the second channel, in case there is a negative or a weak correlation between the above two sources of income, then according to the traditional banking and portfolio theories (Diamond, 1984) any observed increase in the share of fee-generating business in the overall portfolio of banking items reduces the volatility of total earnings via diversification effects. As a consequence, the level of bank riskiness is reduced. In sum, our results for *SECASSET* and *DERIV* are in line with the effect that Instefjord (2005) highlights according to which banks can achieve enhanced risk-sharing and risk diversification through their exposure to derivative markets. Results also provide support to Van Oordt (2014), who documents that securitisation contributes to a fall in the likelihood of individual bank failure as well as to Wu et al. (2011), who show that securitisation reduces the overall risk of banks.

On the whole, banks which are perceived as TBTF are also Too-Complex-To-Fail (TCTF). Large banking institutions are considered by authorities as being universal banks in the sense that they follow a more decentralised organisational structure and are exposed to all kinds of products. Further, these institutions are viewed as being of high importance for the stability of the financial system. This is in contrast to what holds for small and medium-sized banks, which are less decentralised and mainly focus on the activities of deposit-taking and loan-granting. This overall finding is in line with Hakenes and Schnabel (2010), who show that small banks which are not considered by authorities to be systemically important turn to take higher risk thus increasing their probability of going bankrupt. This phenomenon is more pronounced when the bailout likelihood of the large banks which are protected by the system is increased.

We can now sketch out the profile of banks which are more likely to fail as well as that of banks which are more likely to receive assistance in the case of financial debacle. Regulators are more likely to close a bank if it has inadequate equity capital, illiquid and risky assets, poor management, low levels of earnings, and high sensitivity to market risk. However, not all the aforementioned factors are related to the probability of a bank to be bailed out. The decision to keep a bank afloat is affected by the capital strength of the scrutinised bank, its earnings profile, the liquidity degree of its portfolio, and its sensitivity to market risk. Credit quality and management expertise do not significantly influence regulators in their decision to save a distressed bank. Crucially, a small bank with a simple organisational structure that follows a traditional model of business based on deposits and loans is more likely to fail. On the other hand, a large banking firm with a sophisticated organisational structure which heavily relies on non-traditional banking products to finance its operations has a higher chance to be bailed out. All in all, our results show that the determinants of failures differ from those of bailouts, implying that authorities treat a distressed bank differently in their decision to let it fail or to bail it out.

We now turn to examine the effect of the additional bank-specific variables and that of the environmental variables in the failure and bailout likelihoods by focusing on columns 2a and 2b of Table 4. A bank's political connections (*POLCON*) exert a significantly negative impact on the failure hazard as they lower the relevant probability; on the other hand, *POLCON* is found to increase the bailout probability. Along the same lines, we document that when a bank is more closely connected to regulators (*FEDCON*) then its failure (bailout) probability is significantly reduced (increased). Moreover, the connection to a House member who serves on the finance committees involved in drafting and amending TARP (*COMMIT*) is associated with a statistically significant decrease (increase) in the likelihood of failure (bailout). Further, our results reveal that contributions to political parties campaigns (*CAMP*) significantly lower (boost) the chance of a bank being let to fail (being bailed out). Overall, our results are in line with Dunchin and Sosyura (2012), who suggest that the connections of distressed banks with the political and regulatory authorities was a major determinant in the distribution of TARP funds. By the same token, Bayazitova and Shivdasani (2012) find that TARP infusions were provided to those banks that posed systemic risk, faced high expected financial distress costs, and were politically well-connected.

When a bank is involved as an acquirer in a M&A transaction (*MA*), this significantly reduces its failure likelihood. However, *MA* has no statistically significant impact on the bailout probability. To continue, if a bank is located in a MSA, then it is less likely to fail and more likely to receive financial assistance. The latter finding is confirmed by the geographical characteristics of our data set. Many failed banks are located in rather distant, sparsely populated geographical districts, and concentrate their activities in the mainland close to rural states like, for instance, Iowa, Nebraska, or Utah. On the other hand, most of the Northeastern and Southeastern states (excluding California) which constitute large parts of MSAs have a few bank failures and a large number of bailouts. As regards newly-chartered banks (*DENOVO*), these are found to be more likely to fail; however, the age of a bank does not have any statistically significant impact on the bailout hazard. Further, a bank which is publically traded (*PUBLIC*) is less likely to fail, but more likely to receive financial assistance. This result is in line with the reported effect of *SIZE* as discussed above: larger banks are those which are typically publically traded in contrast with their smaller counterparts which are not listed on the stock exchange market. Lastly, there is no statistically significant association between a bank which is a HC subsidiary (*HC*) and the probabilities under scrutiny.

Regarding the impact of the environmental variables, we document that the level of economic activity (*GDP*) has a statistically negative impact on the failure probability. This suggests that negative GDP growth enhances the chances for a bank to fail. On the other hand, the impact of *GDP* on bailout probability is not statistically significant. A higher inflation rate (*INF*) is significantly associated to a higher risk of failure, whereas no significant relationship is reported between *INF* and the bailout hazard. To continue, *QE* is found not to significantly affect the hazards of failure and bailout. Even though the quantitative easing programmes are designed to inject liquidity in banks and in the economy, to improve asset quality and, in turn, to boost bank profitability through an increase in capital gains, they do not seem to have a direct impact on the examined probabilities in the context of our analysis.

Our results provide strong support to the TMTF effect. If the decision of authorities to close or to bailout a distressed bank is based exclusively on that bank's health, then the *TMTF* variable should not be significantly related to any of the examined probabilities. By contrast, we find that *TMTF* has a positive (negative) and highly significant impact on the failure (bailout) likelihood. Taken together, we claim that, after controlling for individual bank characteristics and other relevant factors, regulators are inclined to financially support a distressed bank to remain afloat instead of letting it go bankrupt in case there are too many banks in distress in the economy.

4.2. In-sample estimation: Dynamic competing risks hazard model vs logit model

We compare the forecasting power of our model with that of the static logit model which is commonly used in the relevant literature. The posterior probabilities of failure and bailout can be derived directly from the following logit model specification:

$$\log\left(\frac{P_{it}^{j}}{1-P_{it}^{j}}\right) = \beta_0 + \beta_g x_{g,it-3}, \tag{14}$$

where $P_{it}^{j} = Prob(y_{it} = 1|x_{it-3})$ is the probability for bank *i* to exit the sample in period *t* due to the event *j* with *j*= 1, 2 where 1 stands for failure and 2 for bailout; $\beta_0$is the vector of constant terms; β_g is the vector of g parameters to be estimated; and $x_{g,it-3}$ is the three-period lagged vector of the same covariates that we use in our baseline model (Equation 8) and are presented in Appendix A. The lag structure (i.e., *t*-3) is determined by two of the most popular selection criteria, namely the Akaike Information Criterion and the Schwarz-Bayesian Information Criterion. The left-hand-side expression in Equation (14) is the log odd's ratio, which measures the probability of bank distress relative to the probability of no distress. When *j*=1, the dependent variable takes the value one for failed banks and the value zero for non-failed banks. In a similar vein, when *j*=2, the dependent variable takes the value one for bailed out banks and the value zero for non-bailed out banks. The estimated slope coefficients measure the impact on the odds of bank failure/bailout of a change in the corresponding explanatory variables. Positive coefficients increase the odd of failure/bailout, while negative coefficients are associated with a decrease in the odd of failure/bailout.

Equation (14) can be estimated by assuming independence of errors across the sample banks and across time. Nevertheless, the violation of this assumption is likely to lead to downward biased estimates of the standard errors of the coefficients. Hence, we employ a heteroskedasticity-robust variance-covariance matrix approach that allows for the possibility of correlated errors within banks. As shown in Table 5, the probabilities of failure and bailout are estimated separately based on CAMELS components and the indicators of systemic importance (columns 1a and 1b, respectively), and also accounting for the additional bank-specific factors and for the environmental variables (column 2a and 2b, respectively).

[INSERT TABLE 5 HERE]

Comparing the in-sample estimation results for the two rival models as presented in Tables 4 and 5, we note that the signs of the fitted coefficients remain largely unchanged. This confirms the positive/negative relationships between the explanatory variables and the two hazards under scrutiny we document in the estimation of our baseline model. Markedly, the level of statistical significance of the majority of the coefficients in the logit regressions is lower compared to the significance of the coefficients in our hazard model. Along the same lines, the goodness-of-fit of the logit models as given by the value of the pseudo R-squared is substantially lower if compared to that of our model.

4.3. Out-of-sample estimation: Dynamic competing risks hazard model vs logit model

We compare the out-of-sample forecasting power of the two rival models by resorting to the decile methodology proposed by Shumway (2001) and Bharath and Shumway (2008). The decile forecasting accuracy test captures a model's ability to predict an event from which actual probabilities of that event can be inferred once the coefficients of the examined model are estimated. In the context of our analysis, all banks are sorted into deciles each quarter from 2009q2 to 2009q4 based on the fitted probability values of our forecasting variables (i.e., model covariates). Forecasts rely on the complete model specification, that is, on the specification that, apart from the CAMELS components and the systemic indicators, also includes the additional bank-specific and environmental factors.[17] Fitted probabilities (or rankings) are created by combining the coefficients from the two rival models estimated using 2003q1-2009q1 data with the data available in each subsequent quarter (i.e., 2009q2, 2009q3, and 2009q4).

Table 6 reports the percentages of the correctly predicted failures (Panel A) and bailouts (Panel B) for both models, which are classified into each of the five highest probability deciles and into the least likely 5 deciles in the quarter in which banks actually failed or were bailed out. The top deciles are expected to provide the highest forecasting ability. The correctly predicted number of failures and bailouts in each probability decile and the relevant cumulative probabilities are also reported in Panels A and B, respectively.

[INSERT TABLE 6 HERE]

As shown in the Panel A, our baseline model is able to classify the 63.90% of failed banks (107 banks) in the highest probability decile at the beginning of the quarter in which they declare bankruptcy, while the logit model is able to classify only the 41.10% of failed institutions (69 banks) in the top decile. Moreover, our model predicts 19.80% of the failures (33 banks) in the second top decile, while logit predicts 14.50% of the failures (24 banks) in this decile. Overall, our dynamic competing risks hazard model predicts 83.70% of failures (140 banks) in the top two deciles, whereas the relevant prediction ability of the logit model is 55.60% (93 banks). By the same token, as displayed in Panel B, our model classifies 80.30% of all bailouts (662 banks) in the highest two probability deciles. The relevant percentage for the logit model equals to 47.50% (391 banks). In sum, the out-of-sample prediction ability of our baseline model clearly outperforms that of logit model.

Our model can be thought of as a binary logit model that includes each bank-quarter as a separate observation. Since our sample banks have 28 quarters of data, approximately 28 times more data is available in the estimation of our model than is available to estimate static models like logit. Therefore, our model produces more efficient out-of-sample forecasts by utilising a much larger range of data. This data results in more precise parameter estimates and superior forecasts. Hence, our dynamic competing risks hazard model appears to be a very suitable and accurate early warning policy tool to be utilised by authorities in the prediction of bank failures and bailouts.

[17] We also run a decile forecasting accuracy test based on the model specification which excludes the additional bank-specific variables and the environmental factors. The results we obtain are similar and are available upon request.

5. Robustness analysis

5.1. In-sample estimation: Robustness checks

Clearly, the first phase of TARP was driven by the most systemically important financial institutions. We, therefore, account for the impact of the involuntary participation in TARP by excluding the nine banks of the first phase from our analysis to alleviate any concerns that the decision of the U.S. Treasury to force those banks to receive financial assistance was based on different motivations.[18] In a similar vein, the biggest bank failure, that of Washington Mutual Bank with $307 billion of assets, is treated as an outlier and is excluded from the set of failed institutions. Washington Mutual was the sixth largest U.S. commercial bank when it failed in September 2008. Bank of America, JP Morgan Chase, Wachovia Bank, Citibank, and Wells Fargo Bank were those five institutions with more assets than Washington Mutual Bank. In fact, no other commercial or savings banking organisation with more than $100 billion of total assets went bankrupt during the crisis. On the other hand, the smallest failed bank held approximately $10 million of assets. By excluding the aforementioned ten banks from our analysis, we manage to remove the impact of extreme values and outliers on the estimates of our model parameters. This is in line with the process followed by Shumway, who winsorises all the covariates at the 1st and 99th percentiles. In addition, we exclude all the banks that were involved in M&As as acquirers from the sample of distressed institutions. The main reason is that these acquisitions may have been a source of distress.[19] In total, we exclude 5 failed and 224 bailed out banks from our initial sample.[20] Hence, the overall number of the former banks is reduced to 162 and that of the latter banks shrinks to 600.

To further enhance the validity of our robustness analysis, we enrich our model specification by incorporating three additional environmental variables in Equation (8). We resort to Herfindahl-Hirschman Index (*HHI*) to measure the degree of market concentration calculated as the sum of squared market shares for each bank i in quarter t using total deposits as the input variable. We also consider for possible discrepancies in the regulatory banking environment

[18] Alternatively, instead of excluding the phase-one TARP banks, we introduce a dummy variable in our model that accounts for these banks. However, the dummy is not found to be statistically significant and, hence, we decide to drop it from our analysis.

[19] We thank an anonymous reviewer for providing this suggestion.

[20] We clarify that the Washington Mutual Bank and the nine banks of the first phase of TARP are part of the 5 failed and the 224 bailed out banks respectively as they all played the role of acquirers at least once during the crisis.

following Cole and White (2012) and Berger et al. (2016). The primary regulatory authority for nationally chartered banks is the Office of the Comptroller of the Currency (*OCC*); for the state-chartered banks, it is the Federal Reserve System (*FRS*); and for the state-chartered banks which are not members of FRS it is the FDIC. We include two dummy variables in our model, *OCC* and *FRS*, keeping the FDIC-regulated banks as the base case to account for any differences in the regulatory framework. All variables which are employed in our robustness analysis as well as the sources used to construct them are summarised in Appendix A.

[INSERT TABLE 7 HERE]

As shown in columns 1a and 1b of Table 7, our estimation results remain robust to the tests we carry out. We corroborate that capital (*CAP1*) is beneficial for banks' health, as it significantly reduces both the probability of failure and that of bailout. In other words, increased leverage is harmful for banks as it undermines their soundness making them vulnerable to economic and financial shocks. We also confirm that when credit quality (*ASSETQLT1*) worsens, the odds of failure becomes higher; however, the bailout probability is not significantly affected by the volume of bad loans. Efficient bank management (*MNGEXP1*) exerts a decreasing effect on the failure probability, but has no statistically significant impact on the bailout probability. To continue, more profitable banks (*EARN1*) as well as those that hold a larger portion of liquid assets (*LQDT1*) are found to have lower failure and bailout probabilities. We also confirm that the level of sensitivity to market risk (*SENSRISK1*) increases both the hazard of failure and that of bailout.

Our results also corroborate the impact of the systemic importance indicators on the examined probabilities, providing further evidence for the validity of the TBTF and the TCTF phenomena. In specific, the estimated coefficients on size (*SIZE*) indicate that the larger a bank is the less likely is to fail and the more likely is to be bailed out. Organisational complexity (*ORGCOMPL*) is negatively linked to the probability of failure and positively related to the odds of bailout, whereas the business model complexity as reflected in the involvement of banks with non-traditional activities (*SECASSET1* and *DERIV1*) significantly decreases the odds of an institution to declare bankruptcy, increasing, at the same time, the odds to receive financial aid.

In line with the results of our main analysis, we also document that better-connected banks are significantly more likely to receive TARP money. On the other hand, a bank's connections with politicians, political parties, or regulators exert a significantly negative impact on failure as they lower the relevant probability. This is to say, regulators are more likely to provide financial support to a distressed banking firm which is well-connected and less likely to let it go bankrupt. The results holds for all the four relevant variables either at the 1% level of significance (*POLCON* and *CAMP*), or at the 5% level (*FEDCON* and *COMMIT*). Importantly, our estimation results remain robust in respect to all the additional bank-specific variables (*MA*, *MSA*, *DENOVO*, *PUBLIC*, and *HC*) we employ in our analysis.

Market concentration (*HHI*) is found to be negatively (positively) associated with the risk of failure (bailout). The relevant coefficients are statistically significant at the 1% and 5% levels, implying that distressed banks are significantly less likely to fail and more likely to receive assistance when the market structure of the banking industry is more concentrated. In line with the results of Cole and White (2012) and Berger et al. (2016), *OCC* is found to have a positive and statistically significant effect on failure probability, which means that nationally chartered banks are more likely to fail. On the other hand, the impact of *OCC* on the bailout hazard is not significant. Further, we report no significant influence on the failure or bailout probabilities that could be explained by *FRS* as a bank's primary regulatory authority. Notably, the coefficients and the levels of statistical significance for the remaining environmental variables (*QE*, *TMTF*, *INF*, and *GDP*) are either the same or very similar with those obtained in our baseline estimation.

We now turn to focus on the in-sample estimation of the logit model, which accounts for the outlier banks, bidders in M&As, and also for the augmented set of environmental variables. As shown in columns 2a and 2b of Table 7, the signs of the estimated coefficients remain the same, endorsing the positive/negative links between the regressors and the two probabilities under examination. Noticeably, the statistical significance of most of the coefficients in the logit regressions is lower compared to that of the fitted coefficients of our robustness hazard model. As regards the goodness-of-fit of the logit models which is reflected in the relevant values of the pseudo R-squared, this is considerably lower compared to that of our model.

5.2. In-sample estimation: Additional robustness checks

In our baseline model specification (Equation 8), we implicitly assume that the heterogeneity among the sample banks is captured by the set of covariates used to forecast bank failure and bank bailout. In case this assumption does not hold true, then our model variables may be characterised by unobserved heterogeneity. This implies that the conditional independence assumption of the Shumway model, which is one of the three assumptions to be met for a hazard model to be consistent, will be violated. This assumption is, in fact, analogous to the common econometric assumption that the model is sufficiently well specified to guarantee that the error terms of different observations are independent of each other. Hence, although we employ a broad spectrum of bank-specific variables in our main analysis that can capture a large portion of heterogeneity among our sample banks, we should consider the possibility that some piece of bank-specific information may have been omitted. To address possible unobserved heterogeneity, we introduce a heterogeneity term ε_i in Equation (8):

$$h_j(t; x(t)) = h_{0j}(t) \exp\left[\beta_j' x(t) + v_j + \varepsilon_i\right], \tag{15}$$

where ε_i stands for the unobserved heterogeneity among banks.[21]

As an additional robustness test, we apply a set of alternative CAMELS components on Equation (8).[22] The main reason is that the components of CAMELS are kept confidential from regulators and, hence, it is crucial to test the sensitivity of our baseline regression results to a set of alternative CAMELS variables. Capital adequacy is measured by the ratio of Tier 1 regulatory capital to total risk-weighted assets (*CAP2*); asset quality is captured by the restructured and outstanding balances of loans and lease financing receivables that the bank has placed in nonaccrual status divided by total loans and leases (*ASSETQLT2*); management expertise is proxied by the total operating income calculated by the sum of interest income and non-interest income as a fraction of the total earning assets (*MNGEXP2*), which is a typical measure of operating efficiency in the banking literature (see, e.g., Lane et al., 1986); the return on equity given by the ratio of total net income to total equity capital is utilised to measure bank earnings (*EARN2*); the ratio of federal funds purchased and securities sold under agreements to repurchase to total assets (*LQDT2*) is employed to measure the degree of liquidity; and the sensitivity to market risk (*SENSRISK2*) is proxied by the market interest rate risk defined as the quarterly standard deviation of the day-to-day 3-month U.S. T-bill rate divided by total earning assets.

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[21] Allowing for heterogeneity may lead to less efficient estimators when datasets are small. Our dataset, however, is large and, hence, any minor loss of efficiency is not considered to be significant.
[22] The alternative set of CAMELS is also applied on Equation (15). The obtained results remain largely the same and are available upon request.

Importantly, our results remain robust to the alternative model specification which takes possible bank heterogeneity into consideration. Results are also robust to the use of the alternative set of CAMELS components. For the sake of brevity, we do not present the results of these robustness checks, which, however, remain available on request.

5.3 Out-of-sample estimation: A robustness test

We now test the robustness of the out-of-sample forecasting ability of the two rival models by applying the Receiver Operating Characteristic curve (ROC curve, henceforth). The ROC curve plots the true positive rate versus the false positive rate for all the sample banks, calculating the trade-off between the Type 1 and Type 2 errors. Type 1 error corresponds to misclassifying a failed (bailed out) bank as a non-failed (non-bailed out) bank. A Type 2 error corresponds to misclassifying a non-distressed bank as a distressed bank. In sum, the ROC curve shows how well each of the two rival models clusters the sample banks into the actual groups of non-distressed, failed, and bailed out banks.

The out-of-sample predictions rely on the coefficients we obtain by estimating the dynamic competing risks hazard model (Equation 15) and the logit model (Equation 14) over the 2003q1-2009q1 period. In the estimation of the logit model, we account for quarterly fixed effects since fixed effects are considered to be the analogue of the unobserved heterogeneity term that we introduced in Equation (15). The estimated coefficients are then applied to data for the subsequent three quarters (i.e., 2009q2 to 2009q4) to test the forecasting accuracy of the two models.[23]

[INSERT FIGURE 1A HERE]

[INSERT FIGURE 1B HERE]

[INSERT FIGURE 2A HERE]

[INSERT FIGURE 2B HERE]

A ROC curve with a perfect forecasting ability would start at the top left corner of at a Type 1 error rate (as shown on the vertical axes in Figures 1a through 2b) of 100% and a Type 2 error rate (as shown on the horizontal axes in Figures 1a through 2b) of 0%, track down the vertical axis to a Type 1 error rate of 0% and a Type 2 error rate of 0%, and then track right across the horizontal axis to a Type 1 error rate of 0% and a Type 2 error rate of 100%. Our model

[23] Like in Section 4.3, the out-of-sample estimations rely on the complete model specification.

demonstrates a higher degree of convexity to the origin as shown in Figures 1a and 2a compared to that of the logit model (Figures 1b and 2b), thus indicating a stronger forecasting power. More specifically, by examining Figures 1a and 1b we can highlight that for a Type 2 error rate of 1% where we misclassify 66 out of 6,611 non-problem banks, the Type 1 error rate is 13.7% (23 out of 167 failures) for our model and 21.0% (35 out of 167 failures) for the logit model. Similarly, for a Type 2 error rate of 5% where we misclassify 331 out of 6,611 banks, the Type 1 error rate is only 2.7% (5 out of 167 failures) for our model and 6.4% (11 out of 167 failures) for logit. Turning to examine Figures 2a and 2b which display the out-of-sample forecasting power of the two rival models for the bailout probability, we note that for a Type 2 error rate of 1%, the Type 1 error rate is 15.4% (127 out of 824 bailouts) for our model and 22.7% (187 out of 824 bailouts) for the logit model. In a similar vein, for a Type 2 error rate of 5%, the Type 1 error rate is 4.1% (34 out of 824 bailouts) for our model and 8.9% (73 out of 824 bailouts) for logit. To sum up, the outcome of the out-of-sample robustness analysis based on the ROC curve is consistent with that received from the decile forecasting accuracy test.[24]

6. Concluding remarks

Numerous banking institutions around the globe faced severe liquidity problems and capital shortages after the eruption of the global financial crisis in mid-to-late 2007. National governments in close cooperation with regulatory authorities spent a vast amount of money to keep many of these institutions afloat with the utmost purpose to protect the financial system from a sort of chain domino defaults and to restore the confidence in it. On the other hand, several distressed banks went bankrupt, incurring a large cost to governments, bank customers, bond holders, market participants, and tax payers.

In this paper, we contribute to the better understanding of the key factors related to the operation of the banking system that led to the recent crisis through the development of an early warning system of bank distress. We resort to the dynamic approach of Shumway (2001) to develop a competing risks hazard model, which considers not only the concept of failure but also

[24] As an additional out-of-sample test of the forecasting accuracy of the two models, we resort to the Root Mean Square Error (RMSE) that provides us with an indication of the accuracy of a forecast by stating that projections with a lower value are preferable. The results of the RMSE test further corroborate the superior predicting ability of our model.

that of bailout. The underlying patterns of distress are analysed based upon a broad spectrum of observable and non-observable bank-specific and environmental determinants.

We provide strong evidence that banking organisations with inadequate capital, illiquid and risky assets, poor management, low levels of earnings and high sensitivity to market conditions have a higher bankruptcy probability. However, not all the aforementioned factors play an important role in the probability of a bank to receive assistance in the case of financial debacle. In specific, management quality, as reflected in the ability of managers to create profits for their banks, does not significantly affect the likelihood of a bank to receive financial aid. Further, the quality of bank assets is not found to be relevant to the bailout likelihood.

Our findings also reveal that large and complex financial institutions are less likely to face a license withdrawal and more likely to be bailed out. Hence, we provide strong evidence on the occurrence of the TBTF and the TCTF phenomena in banking. Moreover, authorities are found to be more prone to provide support to a distressed institution which is well-connected with politicians and political parties and less prone to let it go bankrupt. Crucially, the effects of an additional set of key bank-specific variables together with a set of environmental variables that we employ in our analysis confirm that, on the whole, the determinants of bank failures and those of bailouts differ from each other to a considerable degree. This implies that the authorities treat a bank differently in their decision to let it fail or to bail it out.

Importantly, the forecasting accuracy of the hazard model we develop and apply in our analysis is stronger compared to that of the logit model, which is commonly used in the early warning literature to predict failures. The dynamic nature of our model provides us with the advantage of examining how the probability of a bank becoming distressed may vary over time. This cannot be achieved if a static model like the logit model is used instead. In the context of our research, bank health is allowed to change through time and distress is measured as a function of a broad set of accounting and financial data, bank-specific characteristics, macroeconomic factors, as well as variables reflecting the bank regulatory environment. That is, all the available information is utilised in our model to produce failure and bailout probability estimates for each sample bank at each sample quarter.

In sum, our findings offer valuable insights to policy makers on how to better structure the components of the banking industry with the purpose to reduce bank actions that exert a negative impact on bank soundness and can harm the stability of the financial system. The competing risks hazard model à la Shumway we propose is capable of providing national authorities, bank regulators and supervisors with the necessary signals to distinguish healthy from distressed institutions and to work as an effective mechanism for preventing future welfare losses due to possible failures and bailouts in case of a financial breakdown.

Acknowledgements
The author would like to thank the participants at the International Finance and Banking Society (IFABS) 2011 Conference, the XX International Tor Vergata Conference on Money, Banking and Finance, the 29th Spring International Conference of the French Finance Association, the INFINITI 2012 Conference on International Finance, the European Financial Management Association (EFMA) 2012 Conference, and the Financial Engineering and Banking Society (FEBS) 2013 and 2014 Conferences for their valuable comments and suggestions. The paper has been benefited from discussions with Wolfgang Aussenegg, Ray Barell, Mauro Constantini, Özlem Dursun-de Neef, Franco Fiordelisi, Bill Francis, Georges Gallais-Hamonno, Charles Grant, John Hunter, Kose John, Charles Kahn, Alexandros Kontonikas, Josef Korte, Frank Hong Liu, John Mckernan, Krishna Paudyal, George Pennacchi, Anthony Saunders, Leilei Tang, Chandra Thapa, Patrick Verwijmeren, and Laurent Weill. The author also thanks seminar participants at the University of Glasgow, University of Manchester, University of Strathclyde, and Brunel University. The author would like to express his sincere thanks to the two anonymous reviewers and the Editor of Journal of Financial Stability, Iftekhar Hasan, for their incisive comments.

Appendix A. Variables and data sources

This Appendix presents all the variables we use in the main econometric analysis and in the robustness analysis. The abbreviation of each variable and the sources we utilise to collect the data are also reported.

Variable	Abbreviation	Definition	Data sources
CAMELS components			
Capital adequacy	*CAP1*	The ratio of book equity capital to total assets	Call Reports & Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution
	CAP2	The ratio of regulatory (Tier 1) capital to total risk-weighted assets	
Asset quality	*ASSETQLT1*	The ratio of non-performing loans to total loans and leases	
	ASSETQLT2	The ratio of restructured and outstanding balances of loans and lease financing receivables that the bank has placed in nonaccrual status to total loans and leases	
Management expertise	*MNGEXP1*	Managerial efficiency calculated using the input-oriented DEA model	
	MNGEXP2	The ratio of total operating income calculated as the sum of interest income and non-interest income to total earning assets	
Earnings strength	*EARN1*	The ratio of total net income given by the difference between total interest plus non-interest income and total interest plus non-interest expense to total assets	
	EARN2	The ratio of total net income given by the difference between total interest plus non-interest income and total interest plus non-interest expense to equity capital	
Liquidity	*LQDT1*	The ratio of cash and balances due from depository institutions to total deposits	
	LQDT2	The ratio of federal funds purchased and securities sold under agreements to repurchase to total assets	
Sensitivity to market risk	*SENSRISK1*	The change in the slope of the yield curve (given by the change in the quarterly difference between the 10-year U.S. T-bill rate and the 3-month U.S. T-bill rate) divided by total earning assets	Call Reports & Federal Reserve Board & U.S. Department of the Treasury
	SENSRISK2	Market interest rate risk (defined as the quarterly standard deviation of the day-to-day 3-month U.S. T-bill rate) divided by total earning assets	
Systemic importance			
Bank size	*SIZE*	The natural logarithm of the book value of total assets	Call Reports & Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution
Organisational complexity	*ORGCOMPL*	The log of the product of the number of branches that each sample bank has and the number of U.S. states in which the bank has branches	
Business complexity	*SECASSET*	The ratio of the outstanding principal balance of loans, leases, and all relevant assets securitised and sold to other financial institutions with recourse or other credit enhancements to total assets	
	DERIV	The ratio of the total amount of the outstanding derivative contracts to total equity capital	

Additional bank-specific variables			
Political connections	*POLCON*	A dummy that equals one if a bank has employed, or is currently employing an individual who is also employed or has been employed in the federal government or appointed to a government advisory board, a congressional or presidential cabinet entity, or an independent commission	Centre for Responsive Politics (CRP)'s Revolving Door
Federal connections	*FEDCON*	A dummy that is equal to unity if an executive at a sample bank was on the board of directors of one of the 12 Federal Reserve Banks or one of their branches either in 2008 or 2009	Federal Reserve & BoardEx
Political commitments	*COMMIT*	A dummy that equals one if a sample bank is headquartered in a district of a House member who served on the key finance committees involved in drafting and amending TARP either in 2008 or 2009	House of Representative, U.S. Census Bureau & U.S. Library of Congress
Campaign contributions	*CAMP*	A dummy that takes the value of one if a sample bank has made PAC contributions in the election cycle for the 2008 congressional election to the members of the Subcommittee on Financial Institutions and the Subcommittee on Capital Markets	Federal Election Commission Political Action Committees (PACs)
M&A transactions	*MA*	A dummy which is equal to unity if a bank is involved in a M&A transaction as an acquirer	M&As database/Federal Reserve Bank of Chicago
Bank location	*MSA*	A dummy indicating whether a bank is located in a Metropolitan Statistical Area or not	Call Reports & U.S. Office of Management and Budget
Newly-chartered bank	*DENOVO*	A dummy indicating a bank which is less than five years old	Call Reports
Listed bank	*PUBLIC*	A dummy which is equal to unity if a bank is listed on the stock exchange market	Center for Research in Security Prices (CRSP)
HC affiliation	*HC*	A dummy indicating whether a bank is a Holding Company subsidiary	Call Reports
Environmental variables			
Quantitative Easing	*QE*	A dummy showing the first round of quantitative easing programme in U.S.	Federal Reserve
Too-Many-To-Fail	*TMTF*	The average capital ratio (total equity capital to total assets) of other banks in the economy weighted by bank total assets	Call Reports
Inflation rate	*INF*	The quarterly change in the U.S. Consumer Price Index (CPI)	Bureau of Labor Statistics, U.S. Department of Labor
Economic growth	*GDP*	GDP output gap	Bureau of Economic Analysis, U.S. Department of Commerce

Market concentration	*HHI*	Herfindahl-Hirschman Index calculated as the sum of squared market shares for each sample bank in each quarter using total deposits as the input variable	Call Reports
Primary regulator for national banks	*OCC*	A dummy indicating whether a bank is a national bank and, as such, is regulated by the OCC	
Primary regulator for state-chartered banks	*FRS*	A dummy indicating whether a sample bank is a state-chartered bank and, as such, is regulated by the FRS	
Distress indicator			
Z-score	*Z*	The sum of *EARN1* and *CAP1* divided by the standard deviation of *EARN1*	Call Reports
Managerial efficiency			
Total loans	*y1*	The sum of commercial, construction, industrial, individual and real estate loans	Call Reports & Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution
Total deposits	*y2*	The sum of total transaction deposit accounts, non-transaction savings deposits, and total time deposits	
Other earning assets	*y3*	The sum of income-earned assets other than loans and the net deferred income taxes	
Total non-interest income	*y4*	The sum of income from fiduciary activities, service charges on deposit accounts, trading fees and income from foreign exchange transactions and from assets held in trading accounts, and other non-interest income	
Price of borrowed funds	*w1*	The ratio of total interest expense to total deposits and other borrowed money	
Price of labour	*w2*	The ratio of total salaries and benefits to the number of full-time employees	
Price of physical capital	*w3*	The ratio of expenses for premises and fixed assets to the dollar amount of premises and fixed assets	

Appendix B. Estimation of Managerial Efficiency

To estimate managerial efficiency (*MNGEXP1*), we employ the Data Envelopment Analysis (DEA) model. DEA model can be computed either as input- or output-oriented. The input-oriented DEA model shows by how much input quantities can be reduced without varying the output quantities produced. Similarly, the output-oriented DEA model assesses by how much output quantities can be proportionally increased without changing the input quantities used. Both output- and input-oriented models identify the same set of efficient/inefficient bank management. Nevertheless, even though the two approaches provide the same results under constant returns to scale, they give different values under variable returns to scale.[25]

We assume that for the n sample banks, there exist Q inputs producing M outputs. Hence, each bank i uses a nonnegative vector of inputs denoted by $w^i = (w_1^i, w_2^i, \dots, w_q^i) \in R_+^Q$ to produce a nonnegative vector of outputs, denoted by $y^i = (y_1^i, y_2^i, \dots, y_m^i) \in R_+^M$, where: i = 1, 2,…, n; q = 1, 2,…, Q; and m = 1, 2,…, M. The production technology, $F = \{(y, w): w\ can\ produce\ y\}$, describes the set of feasible input-output vectors. The input sets of production technology $L(y) = \{w: (y, w) \in F\}$ describe the sets of input vectors which are feasible for each output vector.

To measure the variable returns to scale managerial cost efficiency (*MNGEXP1*), we resort to the following input-oriented DEA model, where inputs are minimised and outputs are held at constant levels. Below, we sketch out the optimisation (minimisation) problem of bank$_1$'s (i=1) cost inefficiency. Note that each bank i faces the same optimisation problem.

$$MNGEXP1_1^* = \min(-MNGEXP1_1),\ \ s.t.\ \ \sum_{i=1}^{N} \lambda_i w_{iq} \leq (MNGEXP1_1)(w_{1q}) \quad \text{(B1)}$$

$$\sum_{i=1}^{N} \lambda_i y_{im} \geq y_{1m} \quad \text{(B2)}$$

$$\sum_{i=1}^{N} \lambda_i = 1 \quad \text{(B3)}$$

$$\lambda_i \geq 0 \quad \text{(B4)}$$

In Equations (B1- B4), w_{1q} and y_{1m} are the qth input and mth output for bank$_1$, respectively; the convexity constraint given by Equation (B3) accounts for the variable returns to scale, where λ_i stands for the activity vector and denotes the intensity levels at which the total

[25] For a detailed discussion on the differences between input- and output-oriented DEA models, the interested reader can refer to Coelli et al. (2005).

observations are conducted. This approach, through the convexity constraint, forms a convex hull of intersecting planes, since the frontier production plane is defined by combining a set of actual production planes. If $MNGEXP1_1^*$ is equal to unity, then the optimal efficiency score is achieved for $bank_1$. This shows that the levels of inputs used cannot be proportionally improved given the output levels, indicating that $bank_1$ lies upon the cost efficiency frontier. If, on the other hand, $MNGEXP1_1$ is less than unity the management of $bank_1$ is considered to be inefficient. The more $MNGEXP1_1$ deviates from the unity, the less efficient the management of $bank_1$ becomes.

An important concern in the estimation of *MNGEXP1* is the definition of inputs and outputs. This essentially depends on the specific role that deposits play in the overall business model of banks. The relevant literature addresses this issue by traditionally referring to two approaches: the intermediation (or asset) approach, and the production (or value-added) approach.[26] Under the former approach, financial firms are viewed as intermediaries which transform deposits and purchased funds into loans and other earning assets. That is, liabilities and physical factors are treated as inputs, while assets are treated as outputs. The production approach, on the other hand, regards financial institutions as producers of services for account holders, measuring output with the number of transactions or documents processed over a given period of time. Therefore, deposits are encompassed in the output and not in the input vector, which exclusively consists of physical entities.

Berger and Humphrey (1991) proposed a third approach, the modified production approach, which, contrary to the aforementioned traditional approaches, captures the dual role of bank deposits. This third approach is regarded as a combination of the intermediation and production approaches, as it enables the consideration of both the input and output characteristics of deposits in the cost function. More specifically, the price of deposits is considered to be an input, whereas the volume of deposits is accounted as an output. Under this specification, banks are assumed to provide intermediation and loan services as well as payment, liquidity, and safekeeping services at the same time. Hence, it can be argued that the latter approach describes the key bank activity of deposit-taking in a more complete manner thereby providing a closer representation of reality.

[26] See Berger and Humphrey (1997) for a detailed analysis of the advantages and the disadvantages of each of the two approaches.

We adopt the modified production approach to define inputs and outputs in the estimation of *MNGEXP1*. We specify four variable outputs, namely total loans (y_1), calculated as the sum of commercial, construction, industrial, individual and real estate loans; total deposits (y_2), which is the sum of total transaction deposit accounts, non-transaction savings deposits, and total time deposits; other earning assets (y_3), expressed as the sum of income-earned assets other than loans and the net deferred income taxes; and the total non-interest income (y_4) which is the sum of income from fiduciary activities, service charges on deposit accounts, trading fees and income from foreign exchange transactions and from assets held in trading accounts plus other non-interest income.

Regarding the inputs we employ in the estimation of *MNGEXP1*, we consider borrowed funds, labour, and physical capital. The price of borrowed funds (w_1) is defined as the ratio of total interest expense scaled by total deposits and other borrowed money; the price of labour (w_2) is calculated by dividing total salaries and benefits by the number of employees; and the price of physical capital (w_3), which is equal to the expenses for premises and fixed assets divided by the dollar amount of premises and fixed assets.

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Table 1. Summary statistics and univariate analysis: CAMELS and systemic importance indicators

This table presents the summary statistics, reporting the means and the standard deviations of the six components of CAMELS ratings, i.e., capital strength (*CAP1*), asset quality (*ASSETQLT1*), quality of management (*MNGEXP1*), earnings strength (*EARN1*), degree of liquidity (*LQDT1*), and sensitivity to market risk (*SENSRISK1*), as well as the means and the standard deviations of the systemic importance indicators, i.e., bank size (*SIZE*), organisational complexity (*ORGCOMPL*), securitisation activity (*SECASSET*), exposure to derivative products (*DERIV*) for the non-distressed, failed, and bailed out banks. The results of a univariate analysis for the mean differences of the aforementioned variables amongst the three banking groups are also presented; the values of a *t*-test that captures the statistical differences in the means are reported in parentheses. All observations are on bank level and constitute average bank-quarter observations over the pre-crisis period (2003q1-2007q3). The description of variables and the relevant data sources are provided in Appendix A. ***, and ** indicate statistical significance at the 1%, and 5% level, respectively.

	Non-distressed (obs=6,611)	Failed (obs=167)	Bailed out (obs=824)	Non-distressed vs Failed	Non-distressed vs Bailed out	Failed vs Bailed out
Variables	Mean (Stdev)	Mean (Stdev)	Mean (Stdev)	Mean diff. (*t*-statistics)	Mean diff. (*t*-statistics)	Mean diff. (*t*-statistics)
CAP1 (%)	12.63 (7.09)	10.17 (5.19)	9.23 (6.79)	2.46*** (6.02)	3.40*** (7.12)	0.94*** (6.97)
ASSETQLT1 (%)	0.58 (9.38)	1.40 (14.62)	1.92 (16.73)	-0.82*** (-4.23)	-1.34*** (-6.14)	-0.52*** (-7.86)
MNGEXP1	0.79 (2.90)	0.77 (2.31)	0.64 (9.41)	0.02 (1.28)	0.15** (1.99)	0.13** (2.05)
EARN1 (%)	0.81 (3.62)	0.27 (2.59)	0.14 (7.87)	0.54*** (3.85)	0.67*** (4.89)	0.13*** (3.42)
LQDT1 (%)	4.74 (5.38)	3.01 (5.97)	2.01 (10.43)	1.73*** (3.40)	2.73*** (4.01)	1.00*** (4.89)
SENSRISK1 (%)	10.77 (7.49)	10.68 (6.82)	17.18 (10.63)	0.09 (1.42)	-6.41** (-2.00)	-6.50** (-1.96)
SIZE (in $bn)	0.86 (230.84)	0.89 (185.03)	9.98 (527.18)	-0.03 (-1.29)	-8.12*** (-6.52)	-8.09*** (-8.96)
ORGCOMPL	1.19 (138.01)	1.40 (107.14)	1.64 (91.59)	-0.21 (-2.06)**	-0.45 (-3.68)***	-0.24 (-1.63)*
SECASSET (%)	10.23 (39.26)	9.89 (27.42)	17.32 (12.82)	0.34 (1.27)	-7.09*** (-6.29)	-7.43*** (-8.33)
DERIV (%)	8.14 (43.77)	7.93 (30.58)	21.63 (11.82)	0.21 (1.38)	-13.49*** (-4.11)	-13.70*** (-6.55)

Table 2. Summary statistics: Additional bank-specific variables

This table presents the summary statistics, reporting the means, medians, and standard deviations for the additional bank-specific variables we employ in our analysis. These variables are: a dummy capturing the political connections of banks (*POLCON*); a dummy for the connections of banks with the regulatory authorities (*FEDCON*); a dummy that shows if a sample bank is headquartered in a district of a House member who served on the key finance committees (*COMMIT*); a dummy for banks which made PAC contributions in the 2008 elections (*CAMP*); a dummy for the acquirer banks in M&A transactions (*MA*); a dummy showing whether a bank is located in a MSA or in a rural county (*MSA*); a dummy for newly-chartered banks (*DENOVO*); a dummy for banks which are listed on the stock exchange (*PUBLIC*); and a dummy indicating whether a bank is a subsidiary of a HC (*HC*). All observations are on bank level, constitute bank-quarter observations, and cover the entire data period that extends from 2003q1 to 2009q4. The description of the variables and the relevant data sources are provided in Appendix A. *** denotes that the mean of failed banks is significantly different from that of bailed out banks at the 1% level; ** denotes that the mean of failed banks is significantly different from that of bailed out banks at the 5% level.

	Non-distressed banks (obs=6,611)			Failed banks (obs=167)			Bailed out banks (obs=824)		
Variable	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev
POLCON	0.0361	0.0000	11.28	0.0170***	0.0000	7.94	0.0738	0.0000	12.54
FEDCON	0.0389	0.0000	49.31	0.0181***	0.0000	13.92	0.0631	0.0000	10.95
COMMIT	0.0410	0.0000	32.84	0.0294**	00000	20.17	0.0936	0.0000	7.68
CAMP	0.0205	0.0168	37.94	0.0135***	0.0089	3.79	0.0542	0.0493	3.15
MA	0.0840	0.0000	9.33	0.0280***	0.0000	3.41	0.2724	1.0000	3.02
MSA	0.5368	1.0000	10.75	0.4193**	0.0000	8.94	0.7141	1.0000	10.69
DE NOVO	0.0311	0.0000	18.73	0.0807***	0.0000	23.02	0.0320	0.0000	31.84
PUBLIC	0.0395	0.0000	26.94	0.0278***	0.0000	11.81	0.0756	0.0000	12.70
HC	0.2239	0.0000	23.06	0.1062**	0.0000	5.44	0.6268	1.0000	5.62

Table 3. Level of individual bank distress

This table reports the level of individual bank distress proxied by Z-score (*Z*). *Z* is measured for each sample bank and for each quarter in the crisis period (i.e., 2007q4 to 2009q4). In the case of failed and bailed out banks, *Z* is measured for each quarter prior to the failure or bailout quarter, respectively. The summary (average) *Z* is then computed for each bank over the examined period and each *Z* is assigned to a decile. All banks are sorted in deciles based on their summary *Z*. The number of banks as well as the relevant percentage for each of the three banking groups by decile of distress is calculated and reported. Banks in the top 10 percent (i.e., in Decile 1) achieve the highest Z-scores that reflect the lowest levels of distress; banks in the lowest 10 percent (i.e., in Decile 10) have the lowest Z-scores which reflect the highest distress levels.

	Failed banks		Bailed out banks		Non-distressed banks	
Decile	Number of banks	Percentage (%)	Number of banks	Percentage (%)	Number of banks	Percentage (%)
1	0	0.00	44	5.34	3,459	52.32
2	1	0.60	3	0.37	1,132	17.12
3	0	0.00	8	0.97	891	13.48
4	4	2.39	9	1.09	308	4.66
5	3	1.80	10	1.21	152	2.30
6	5	2.99	1	0.12	218	3.30
7	3	1.80	51	6.19	102	1.54
8	8	4.79	73	8.86	117	1.77
9	29	17.37	207	25.12	95	1.44
10	114	68.26	418	50.73	137	2.07
TOTAL	167	100.00	824	100.00	6,611	100.00

Table 4. In-sample estimation: Dynamic competing risks hazard model

This table reports the results from the in-sample estimation of the dynamic competing risks hazard model with two types of bank distress, i.e., failure and bailout, as presented in Equation (8). The dependent variable equals to one if a bank fails (columns 1a and 2a), or if it is bailed out (columns 1b and 2b) and zero otherwise. The non-distressed banks constitute the holdout group in the estimation. Two different specifications of Equation (8) are estimated: the first specification, as presented in columns 1a and 1b, considers the CAMELS components (capital strength (*CAP1*), asset quality (*ASSETQLT1*), management expertise (*MNGEXP1*), earnings strength (*EARN1*), degree of liquidity (*LQDT1*), and sensitivity to market risk (*SENSRISK1*)), together with the indicators of systemic importance (bank size (*SIZE*), organisational complexity (*ORGCOMPL*), securitisation activity (*SECASSET*), and exposure to derivative products (*DERIV*)); the second specification presented in columns 2a and 2b also accounts for the additional bank-specific factors (political connections (*POLCON*), connections with regulators (*FEDCON*), connections with House members (*COMMIT*), contributions to federal political campaigns (*CAMP*), acquirer banks in M&A transactions (*MA*), location in MSA or in a rural county (*MSA*), newly-chartered banks (*DENOVO*), listed banks (*PUBLIC*), holding company subsidiaries (*HC*)), as well as for the environmental variables (quantitative easing (*QE*), Too-Many-To-Fail effect (*TMTF*), price level (*INF*), and economic growth (*GDP*)).The coefficients for the two types of distress are jointly estimated under both model specifications. All variables and their data sources are described in Appendix A. Observations are on bank level, constitute bank-quarter observations, and cover the entire data period, which extends from 2003q1 to 2009q4. Heteroskedasticity-robust Huber-White *t*-statistics are reported below the estimated coefficient values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Type of distress			
	Failure (1a)	Bailout (1b)	Failure (2a)	Bailout (2b)
Variables				
CAP1	-1.77*** (-3.01)	-1.58*** (-2.99)	-1.68*** (-3.82)	-1.50*** (-4.12)
ASSETQLT1	1.39*** (2.78)	0.92 (1.37)	1.27*** (3.56)	0.85 (1.55)

MNGEXP1	-1.96** (-2.04)	1.19 (1.28)	-1.90** (-2.53)	1.05 (1.49)
EARN1	-1.43*** (-3.12)	-2.11** (-2.08)	-1.27*** (-4.05)	-2.01** (-2.45)
LQDT1	-1.59** (-1.96)	-1.37** (-1.95)	-1.41*** (-2.76)	-1.20** (-2.41)
SENSRISK1	0.95** (2.20)	1.10** (2.23)	0.85** (2.42)	1.04*** (2.69)
SIZE	-1.33*** (-3.44)	1.39*** (2.97)	-1.49*** (-4.79)	1.58*** (4.35)
ORGCOMPL	-0.71* (-1.69)	1.20* (1.75)	-0.62* (-1.87)	1.07** (2.19)
SECASSET	-2.14*** (-2.78)	5.62** (2.11)	-2.19*** (-4.05)	6.13*** (3.48)
DERIV	-3.30** (-1.96)	5.89*** (3.10)	-3.07*** (-2.79)	5.82*** (4.02)
POLCON			-2.11*** (-4.94)	2.82*** (3.32)
FEDCON			-1.17** (-2.31)	0.94** (2.15)
COMMIT			-0.71** (-2.26)	1.11** (2.08)
CAMP			-2.83*** (-4.28)	3.38*** (3.10)
MA			-0.39*** (-3.24)	-0.23 (-1.48)
MSA			-0.07** (-2.35)	0.12*** (3.62)
DENOVO			0.25** (2.41)	0.47 (1.52)
PUBLIC			-0.13** (-2.49)	0.09** (2.36)
HC			0.04 (0.63)	0.03 (0.82)
QE			0.52 (1.28)	0.39 (0.94)
TMTF			2.95*** (3.41)	-3.05** (-2.38)
INF			0.17** (1.99)	-0.19 (-1.24)
GDP			-0.24** (-2.38)	-0.07 (-1.20)

Pseudo R^2 (%)	35.52	44.72
# banks (*n*)	7,602	7,597

Table 5. In-sample estimation: Logit model

This table reports the results from the in-sample estimation of the logit model as presented in Equation (14). The dependent variable equals to one if a bank fails (columns 1a and 2a), or if it is bailed out (columns 1b and 2b) and zero otherwise. The non-distressed banks constitute the holdout group in the estimation. The probabilities of failure and bailout are estimated separately and presented in columns 1a and 1b based on CAMELS components (capital strength (*CAP1*), asset quality (*ASSETQLT1*), management expertise (*MNGEXP1*), earnings strength (*EARN1*), degree of liquidity (*LQDT1*), and sensitivity to market risk (*SENSRISK1*)), and the indicators of systemic importance (bank size (*SIZE*), organisational complexity (*ORGCOMPL*), securitisation activity (*SECASSET*), and exposure to derivative products (*DERIV*)). In the estimations presented in columns 2a and 2b, we also account for the additional bank-specific factors (political connections (*POLCON*), connections with regulators (*FEDCON*), connections with House members (*COMMIT*), contributions to federal political campaigns (*CAMP*), acquirer banks in M&A transactions (*MA*), location in MSA or in a rural county (*MSA*), newly-chartered banks (*DENOVO*)), as well as for the environmental variables (quantitative easing (*QE*), Too-Many-To-Fail effect (*TMTF*), price level (*INF*), and economic growth (*GDP*)). All variables and their data sources are described in Appendix A. Observations are on bank level, constitute bank-quarter observations, and cover the entire data period, which extends from 2003q1 to 2009q4. A constant term is included in the model, but is not reported in the table. Heteroskedasticity-robust Huber-White *t*-statistics are reported below the estimated coefficient values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Type of distress			
	Failure (1a)	Bailout (1b)	Failure (2a)	Bailout (2b)
Variables				
CAP1	-1.59** (-2.34)	-1.37** (-2.40)	-1.60** (-2.52)	-1.47*** (-2.86)
ASSETQLT1	1.31** (2.26)	0.94 (1.19)	1.10*** (2.78)	0.74 (1.13)
MNGEXP1	-2.20* (-1.81)	1.36 (1.19)	-1.87** (-2.08)	1.26 (1.24)
EARN1	-1.29** (-2.30)	-1.87* (-1.69)	-1.46*** (-3.05)	-2.14* (-1.80)
LQDT1	-1.63* (-1.85)	-1.45* (-1.72)	-1.22** (-2.19)	-1.48** (-1.96)
SENSRISK1	1.17* (1.80)	1.26** (1.97)	0.93** (2.04)	1.17** (2.28)
SIZE	-1.24*** (-2.96)	1.35** (2.32)	-1.33*** (-3.79)	1.31*** (3.41)
ORGCOMPL	-0.58 (-1.30)	0.94* (1.68)	-0.50* (-1.71)	0.93* (1.89)
SECASSET	-1.98** (-2.30)	5.27* (1.84)	-2.12*** (-2.74)	4.98** (2.31)

DERIV	-3.36* (-1.81)	5.99** (2.24)	-3.02* (-1.89)	5.86*** (2.98)
POLCON			-3.11*** (-4.19)	3.55** (2.51)
FEDCON			-0.95** (-1.98)	0.73* (1.82)
COMMIT			-0.54** (-2.00)	0.88* (1.85)
CAMP			-3.18*** (-2.69)	2.76*** (2.58)
MA			-0.25** (-2.11)	-0.18 (-1.19)
MSA			-0.06* (-1.85)	0.09** (2.48)
DENOVO			0.21* (1.89)	0.50 (1.45)
PUBLIC			-0.13** (-2.18)	0.09* (1.84)
HC			0.06 (1.04)	0.03 (0.99)
QE			0.52 (1.28)	0.39 (0.94)
TMTF			3.27*** (2.70)	-2.61** (-2.07)
INF			0.16* (1.71)	-0.22 (-0.79)
GDP			-0.20** (-2.01)	-0.09 (-0.87)
Pseudo R^2(%)	19.98	21.04	26.78	27.90
# banks (*n*)	7,602	7,602	7,597	7,597

Table 6. Out-of-sample decile forecasting accuracy test

This table presents a comparison of the out-of-sample forecasting power between the dynamic competing risks hazard model and the logit model based on the decile forecasting accuracy test. Results rely on the complete model specification, that is, on the specification that, apart from the CAMELS components and the systemic indicators, also considers the additional bank-specific variables and the environmental factors. All banks are sorted into deciles each quarter from 2009q2 to 2009q4 based on the fitted probability values of the forecasting variables. Fitted probabilities are created by combining the coefficients from the two rival models estimated using 2003q1-2009q1 data with the data available in each subsequent quarter (i.e., 2009q2, 2009q3, and 2009q4). The percentages of the correctly predicted failures and bailouts for both models, which are classified into each of the five highest probability deciles and into the least likely five deciles in the quarter in which banks actually failed or were bailed out are presented in Panels A and B, respectively. The correctly predicted number of failures and bailouts in each probability decile and the relevant cumulative probabilities are also reported in Panels A and B, respectively. The total number of failures in our sample is 167, and that of bailouts is 824.

Panel A: Bank failures

	Dynamic competing risks hazard model			Logit model		
Decile	Prob. (%)	Cum Prob. (%)	Failures	Prob. (%)	Cum Prob. (%)	Failures
1	63.90	63.90	107	41.10	41.10	69
2	19.80	83.70	33	14.50	55.60	24
3	5.10	88.80	9	16.80	72.40	28
4	3.20	92.00	5	11.30	83.70	19
5	2.40	94.40	4	6.2	89.90	10
6-10	5.60	100.00	9	10.10	100.00	17
			167			167

Panel B: Bank bailouts

	Dynamic competing risks hazard model			Logit model		
Decile	Prob. (%)	Cum Prob. (%)	Bailouts	Prob. (%)	Cum Prob. (%)	Bailouts
1	61.70	61.70	509	35.60	35.60	293
2	18.60	80.30	153	11.90	47.50	98
3	5.00	85.30	41	13.10	60.60	108
4	4.10	89.40	34	19.50	80.10	161
5	0.60	90.00	5	8.80	88.90	73
6-10	10.00	100.00	82	11.10	100.00	91
			824			824

Table 7. In-sample estimation: Robustness checks

Columns 1a and 1b report the robustness results from the in-sample estimation of our dynamic competing risks hazard model (Equation 8) with two types of bank distress: failure and bailout. Columns 2a and 2b report the robustness results from the in-sample estimation of the logit model (Equation 14). The dependent variable equals to one if a bank fails (columns 1a and 2a), or if it is bailed out (columns 1b and 2b) and zero otherwise. The non-distressed banks constitute the holdout group in all estimations. The nine banks of the first phase of TARP, the largest failed bank (Washington Mutual Bank), and the distressed banks that were involved in M&As as acquirers are all excluded from the estimations. The coefficients for the two types of distress are jointly estimated in the dynamic competing risks hazard model, while the coefficients in the logit model are estimated separately. The covariates include: the CAMELS components (capital strength (*CAP1*), asset quality (*ASSETQLT1*), management expertise (*MNGEXP1*), earnings strength (*EARN1*), degree of liquidity (*LQDT1*), and sensitivity to market risk (*SENSRISK1*)); the indicators of systemic importance (bank size (*SIZE*), organisational complexity (*ORGCOMPL*), securitisation activity (*SECASSET*), and exposure to derivative products (*DERIV*)); the additional bank-specific factors (political connections (*POLCON*), connections with regulators (*FEDCON*), connections with House members (*COMMIT*), contributions to federal political campaigns (*CAMP*), acquirer banks in M&A transactions (*MA*), location in MSA or in a rural county (*MSA*), newly-chartered banks (*DENOVO*), listed banks (*PUBLIC*), and bank subsidiaries (*HC*)); and the enhanced set of environmental variables (quantitative easing (*QE*), Too-Many-To-Fail effect (*TMTF*), price level (*INF*), economic growth (*GDP*), market concentration (*HHI*), Office of the Comptroller of the Currency (*OCC*), and Federal Reserve System (*FRS*)). All variables and their data sources are described in Appendix A. Observations are on bank level, constitute bank-quarter observations, and cover the entire data period, which extends from 2003q1 to 2009q4. Heteroskedasticity-robust Huber-White *t*-statistics are reported below the estimated coefficient values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Type of distress			
	Failure (1a)	Bailout (1b)	Failure (2a)	Bailout (2b)
Variables				
CAP1	-1.61*** (-3.49)	-1.56*** (-3.78)	-1.52** (-2.21)	-1.39*** (-2.65)
ASSETQLT1	1.38*** (2.94)	0.92 (1.40)	1.13*** (2.67)	0.77 (0.96)
MNGEXP1	-2.04*** (-2.70)	0.98 (1.53)	-1.99** (-2.19)	1.12 (1.32)
EARN1	-1.38*** (-3.88)	-1.90** (-2.50)	-1.52*** (-2.94)	-2.15* (-1.87)
LQDT1	-1.32*** (-2.65)	-1.28** (-2.10)	-1.29** (-2.08)	-1.54* (-1.88)
SENSRISK1	1.06** (2.47)	1.09*** (2.82)	1.18** (2.10)	1.23** (2.31)
SIZE	-1.29*** (-4.37)	1.64*** (3.98)	-1.18*** (-3.33)	1.40*** (3.09)
ORGCOMPL	-0.65* (-1.82)	1.13** (2.07)	-0.52* (-1.67)	1.01* (1.74)
SECASSET	-2.30*** (-3.86)	5.88*** (3.31)	-2.21*** (-2.67)	4.55** (2.19)
DERIV	-2.99*** (-2.73)	5.89*** (3.80)	-2.90* (-1.78)	5.92*** (2.84)

POLCON	-2.14*** (-4.77)	2.70*** (3.18)	-3.10*** (-3.95)	3.44** (2.32)
FEDCON	-1.06** (-2.18)	1.03** (1.99)	-0.89** (-1.96)	0.82* (1.69)
COMMIT	-0.80** (-2.18)	1.19** (2.01)	-0.61** (-1.97)	0.92* (1.76)
CAMP	-3.02*** (-4.25)	3.45*** (2.94)	-3.22*** (-2.89)	2.83*** (2.69)
MA	-0.37*** (-2.96)	-0.19 (-1.37)	-0.22** (-2.02)	-0.17 (-1.16)
MSA	-0.06** (-2.29)	0.10*** (3.51)	-0.06* (-1.72)	0.09** (2.28)
DENOVO	0.23** (2.34)	0.40 (1.38)	0.18* (1.74)	0.46 (1.33)
PUBLIC	-0.11** (-2.40)	0.10** (2.19)	-0.12** (-2.08)	0.11* (1.76)
HC	0.05 (0.68)	0.03 (0.80)	0.06 (0.92)	0.04 (1.05)
QE	0.59 (1.17)	0.41 (0.88)	0.55 (1.22)	0.40 (0.79)
TMTF	3.18*** (3.30)	-2.96** (-2.18)	3.31*** (2.63)	-2.52** (-1.98)
INF	0.20** (1.96)	-0.18 (-1.29)	0.17* (1.67)	-0.24 (-0.85)
GDP	-0.22** (-2.41)	-0.08 (-1.37)	-0.19** (-2.10)	-0.09 (-1.04)
HHI	-2.18*** (-3.92)	1.44** (2.36)	-1.80** (-2.28)	1.27** (2.03)
OCC	1.37** (2.38)	0.42 (1.26)	0.84** (2.07)	0.29 (1.05)
FRS	-0.29 (-0.58)	-0.18 (-0.71)	-0.07 (-0.64)	-0.10 (-0.80)
Pseudo R^2(%)	40.28		24.32	26.11
# banks (*n*)	7,358		7,358	7,358

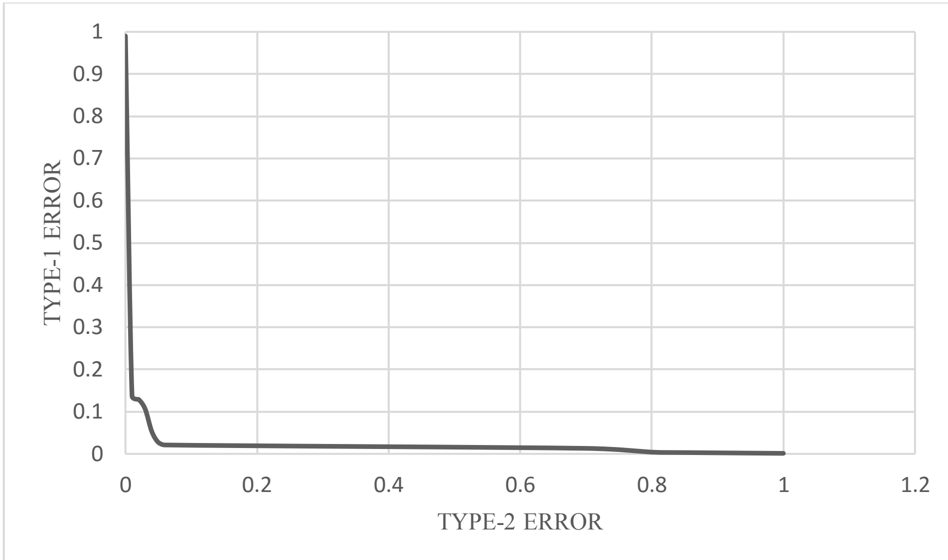

Figure 1a. This figure depicts the ROC curve which describes the trade-off between Type 1 and Type 2 errors for the fitted probability of failure based on the out-of-sample estimation of the dynamic competing risks hazard model (Equation 15) over the 2003q1-2009q1 period. The estimated coefficients are applied to data for the subsequent three quarters (2009q2-2009q4). Type 1 error (vertical axis) corresponds to misclassifying a failed bank as a non-failed bank; Type 2 error (horizontal axis) corresponds to misclassifying a non-distressed bank as a distressed bank.

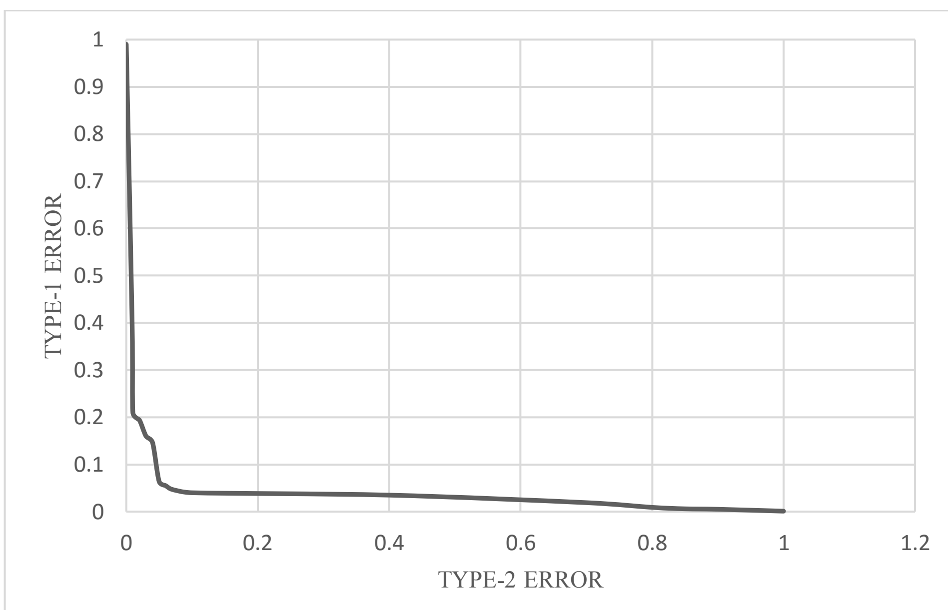

Figure 1b. This figure depicts the ROC curve which describes the trade-off between Type 1 and Type 2 errors for the fitted probability of failure based on the out-of-sample estimation of the logit model (Equation 14) that accounts for quarterly fixed effects over the 2003q1-2009q1 period. The estimated coefficients are applied to data for the subsequent three quarters (2009q2 - 2009q4). Type 1 error (vertical axis) corresponds to misclassifying a failed bank as a non-failed bank; Type 2 error (horizontal axis) corresponds to misclassifying a non-distressed bank as a distressed bank.

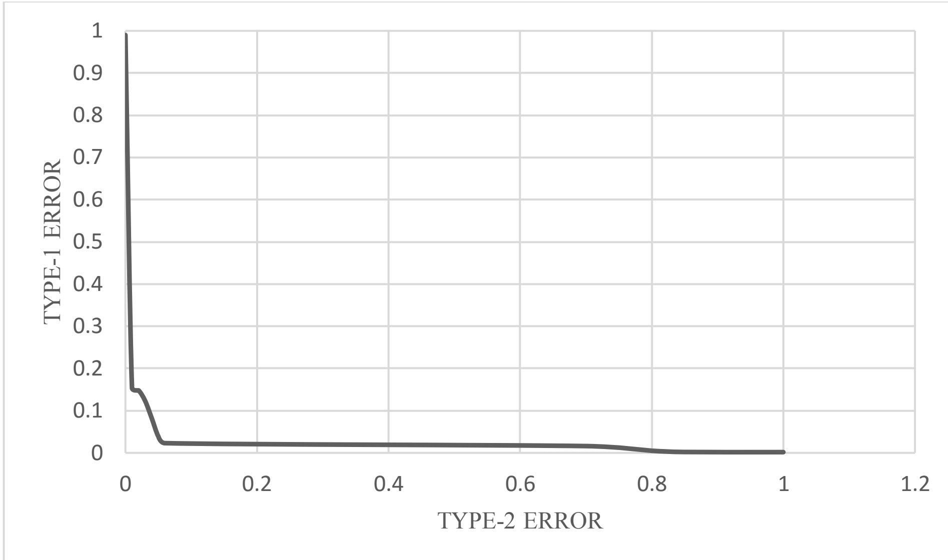

Figure 2a. This figure depicts the ROC curve which describes the trade-off between Type 1 and Type 2 errors for the fitted probability of bailout based on the out-of-sample estimation of the dynamic competing risks hazard model (Equation 15) over the 2003q1-2009q1 period. The estimated coefficients are applied to data for the subsequent three quarters (2009q2-2009q4). Type 1 error (vertical axis) corresponds to misclassifying a bailed out bank as a non-bailed out bank; Type 2 error (horizontal axis) corresponds to misclassifying a non-distressed bank as a distressed bank.

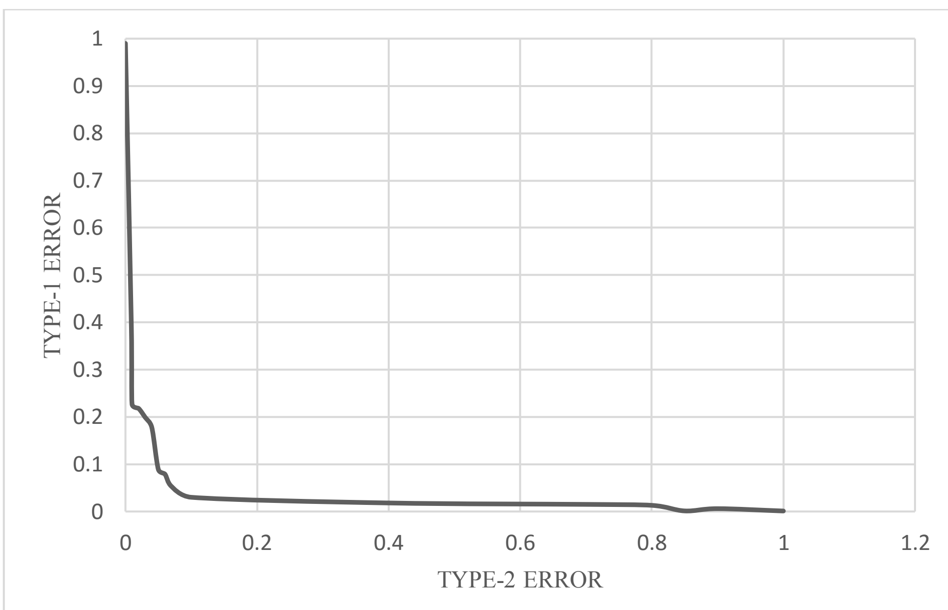

Figure 2b. This figure depicts the ROC curve which describes the trade-off between Type 1 and Type 2 errors for the fitted probability of bailout based on the out-of-sample estimation of the logit model (Equation 14) that accounts for quarterly fixed effects over the 2003q1-2009q1 period. The estimated coefficients are then applied to data for the subsequent three quarters (2009q2-2009q4). Type 1 error (vertical axis) corresponds to misclassifying a bailed out bank as a non-bailed out bank; Type 2 error (horizontal axis) corresponds to misclassifying a non-distressed bank as a distressed bank.