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In this article we provide a summary of empirical results obtained in several economics and operations research papers that attempt to explain, predict, or suggest remedies for financial crises or banking defaults; we also outline the methodologies used in them. We analyze financial and economic circumstances associated with the U.S. subprime mortgage crisis and the global financial turmoil that has led to severe crises in many countries. The intent of this article is to promote future empirical research for preventing bank failures and financial crises.

Keywords: subprime, crisis, mortgage, bank failure, operations research.

JEL codes: G01, G15, G21, C44, C45.

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Introduction

This article reviews econometrics and operations research methods used in the empirical literature to describe, predict, and remedy financial crises and mortgage defaults. Such an interdisciplinary approach is beneficial for future research as many of the methods used in isolation are not capable of accurately predicting financial crises and defaults of financial institutions.

Operations research is a complex and interdisciplinary tool that combines mathematical modeling, statistics, and algorithms. This tool is often employed by managers and managerial scientists. It is based on techniques that seek to determine either optimal or near optimal solutions to complex problems and situations.

Many analytical techniques used in operations research have similarities with functions of the human brain; they are called 'intelligence techniques.' For example, Neural Networks (NN) is the most widely used model among the intelligence techniques.[1] NN models have developed from the field of artificial intelligence and brain modeling. They have mathematical and algorithmic elements that mimic the biological neural networks of the human nervous system. The model uses nonlinear function approximation tools that test the relationship between independent (explanatory) and dependent (to be explained) factors. The method considers an interrelated group of artificial neurons and processes information associated with them using a so-called connectionist approach, where network units are connected by a flow of information. The structure of the model changes based on external or internal information that flows through the network during the learning phase.

Compared to statistical methods, NN have two advantages. The most important of these is that the models make no assumptions about the statistical distribution or properties of the data, and therefore tend to be more useful in practical situations (as most financial data do not meet the statistical requirements of certain statistical models). Another advantage of the NN method is its reliance on nonlinear approaches, so that one can be more accurate when testing complex data patterns. The nonlinearity feature of NN models is important because one can argue that the relation between explanatory factors and the likelihood of default is nonlinear (several statistical

[1] Chen and Shih [1] and Boyacioglu et al. [2].

methodologies, however, are also able to deal with nonlinear relationships between factors in the data).

This paper is related to work of Demirguc-Kunt and Detragiache [3] who review two early warning methods—signals approach and the multivariate probability model—that are frequently used in empirical research analyzing banking crises. Bell and Pain [4] review the usefulness and applicability of the leading indicator models used in the empirical research analyzing and predicting financial crises. The authors note that the models need to be improved in order to be a more useful tool for policymakers and analysts.

In this review we show that statistical techniques are frequently accompanied by intelligence techniques for better model performance in the empirical literature aiming to better predict and analyze defaults and crises. In most of the cases reviewed, models that use operations research techniques alone or in combination with statistical methods predict failures better than statistical models alone. In fact, hybrid intelligence systems, which combine several individual techniques, have recently become very popular.

The paper also provides an analysis of financial and economic circumstances associated with the subprime mortgage crisis. Many researchers, policymakers, journalists, and other individuals blame the subprime mortgage market and its collapse for triggering the global crisis; many also wonder how such a relatively small subprime market could cause so much trouble around the globe, especially in countries that did not get involved with subprime lending or with investment in subprime securities. We provide some insights into this phenomenon.

The subprime credit market in the United States largely consists of subprime mortgages. The term "subprime" usually refers to a loan (mortgage, auto, etc.) that is viewed as riskier than a regular (prime) loan in the eyes of a lender. It is riskier because the expected probability of default for these loans is higher. There are several definitions of subprime available in the industry. A subprime loan can be (i) originated to a borrower with a low credit score and/or history of delinquency or bankruptcy, and/or poor employment history; (ii) originated by lenders specializing in high-cost loans and selling fewer loans to government-sponsored enterprises (not all high-cost loans are subprime, though); (iii) part of subprime securities; and (iv) certain mortgages (e.g., 2/28 or 3/27 "hybrid" mortgages) generally not available in the prime market.[2]

The subprime securitized mortgage market in the United States boomed between 2001 and 2006 and began to collapse in 2007. To better picture the size of this market ($1.8 trillion of U.S. subprime securitized mortgage debt outstanding),[3] it is useful to compare it with the value of the entire mortgage debt in the United States (approximately $11.3 trillion)[4] and the value of securitized mortgage debt ($6.8 trillion).[5] In other words, as of the second quarter of 2008, the subprime securitized market was roughly one-third of the total securitized market in the United States, or approximately 16 percent of the entire U.S. mortgage debt. Before the crisis, it was believed that a market of such small size (relatively to the U.S. total mortgage market) could not cause significant problems outside the subprime sphere even if it were to crash completely. However, we now see a severe ongoing crisis—a crisis that has affected the real economies of many countries in the world, causing recessions, banking and financial crises, and a global credit crunch.

The large effect of the relatively small subprime component of the mortgage market and its collapse was most likely due to the complexity of the market for the securities that were created based on subprime mortgages. The securities were created by pooling individual subprime mortgages together; in addition, the securities themselves were again repackaged and tranched to create more complicated financial instruments.

The mortgage securities were again split into various new tranches, repackaged, re-split and repackaged again many times over. Each stage of the securitization process introduced more leverage for financial institutions and made valuing the holdings of those financial instruments more difficult. All this ultimately resulted in uncertainly about the solvency of a number of large financial firms as over time the market value of the securities was heavily discounted in response to tremors in the housing market itself. Also, the securities were largely traded internationally, which led to spill-overs of the U.S. subprime mortgage crisis and its consequences across the country

[2]See Demyanyk and Van Hemert [5] and Demyanyk [6] for a more detailed description and discussion.

[3]As the total value of subprime securities issued between 2000 and 2007, calculated by Inside Mortgage Finance, 2008.

[4]Total value of mortgages outstanding in 2Q 2008. Source: Inside Mortgage Finance, 2008

[5]Total value of mortgage securities outstanding in 2Q 2008. Source: Inside Mortgage Finance, 2008

borders.

There are two sections in this paper. Section 1 summarizes empirical methodologies and findings of studies that apply econometric techniques. In this section, we outline several analyses of the U.S. subprime market and its collapse. We show that the crisis, even though significant and devastating for many, was not unique in the history of the United States or for other countries around the world. We review the analyses of bank failure and suggested remedies for financial crises in the literature. Section 2 summarizes empirical methodologies used in Operations Research studies analyzing and predicting bank failures. Section 3 concludes.

1 Review of Econometric Analyses of the Subprime Crisis

In this section we analyze the collapse of the subprime mortgage market in the United States and outline factors associated with it.

1.1 Collapse of the U.S. Subprime Mortgage Market

The first signs of the subprime mortgage market collapse in the United States were very high (and unusual even for subprime market) delinquency and foreclosure rates for mortgages originated in 2006 and 2007. High rates of foreclosures, declining home values, borrowers' impaired credit histories, destabilized neighborhoods, numerous vacant and abandoned properties, the absence of mechanisms providing entry into and exit out of the distressed mortgage market (uncertainty froze the market; a limited number of home sales/purchases occurred), and overall economic slowdown created a self-sustaining loop, escape from which was beyond the capacity of market forces to find.

Demyanyk and Van Hemert [5] analyzed the subprime crisis empirically, utilizing a duration statistical model that allows estimating the so-called survival time of mortgage loans, i.e., how long a loan is expected to be current before the very first delinquency (missed payment) or default occurs, conditional on never having been delinquent or in default before. The model also allows controlling for various individual loan and borrower characteristics, as well as macroeconomic circumstances. According to the estimated results, credit score, the cumulative loan-to-value ratio, the mortgage rate, and the house price appreciation have the largest (in absolute terms) marginal effects and are the most important for explaining cross-sectional differences in subprime loan performance. However, according to the same estimated model, the crisis in the subprime mortgage market did not occur *because* housing prices in the United States started declining, as many have conjectured. The crisis had been brewing for at least six consecutive years before signs of it became visible.

The quality of subprime mortgages had been deteriorating monotonically every year since at least 2001; this pattern was masked, however, by house price appreciation. In other words, the quality of loans did not suddenly become much worse just before the defaults occurred—the quality was poor and worsening every year. We were able to observe this inferior quality only when the housing market started slowing down—when bad loans could not hide behind high house appreciation, and when bad loans could no longer be refinanced.

Demyanyk and Van Hemert also show that the above-mentioned monotonic deterioration of subprime mortgages was a (subprime) market-wide phenomenon. They split their sample of all subprime mortgages into the following subsamples: fixed-rate, adjustable-rate (hybrid), purchase-money, cash-out refinancing, mortgages with full documentation, and mortgages with low or no documentation. For each of the subsamples, deterioration of the market is observable. Therefore, one cannot blame the crisis on any single cause, such as a particularly bad loan type or irresponsible lending—there were many causes.

Demyanyk [6] empirically showed that subprime mortgages were, in fact, a temporary phenomenon, i.e., borrowers who took subprime loans seemed to have used mortgages as temporary bridge financing, either in order to speculate on house prices or to improve their credit history. On average, subprime mortgages of any vintage did not last longer than three years: approximately 80 percent of borrowers either prepaid (refinanced or sold their homes) or defaulted on the mortgage contracts within three years of mortgage origination.

Several researchers have found that securitization opened the door to increased subprime lending between 2001 and 2006, which in turn led to reduced incentives for banks to screen borrowers and increased subsequent defaults. For example, Keys et al. [7] investigate the relationship between securitization and screening standards in the context of subprime mortgage-backed securities. Theories of financial intermediation suggest that securitization—the act of converting illiquid loans into liquid securities—could reduce the incentives of financial intermediaries to screen borrowers. Empirically, the authors "exploit a specific rule of thumb [credit score 620] in the lending market to generate an exogenous variation in the ease of securitization and compare the composition and performance of lenders' portfolios around the ad-hoc threshold." They find that "the portfolio that is more likely to be securitized defaults by around 10-25% more than a similar risk profile group with a lower probability of securitization," even after analyzing for "selection on the part of borrowers, lenders, or investors." Their results suggest that securitization does adversely affect the screening incentives of lenders.

Mian and Sufi [8] show that securitization is associated with increased subprime lending and subsequent defaults. More specifically, the authors show that geographical areas (in this case, zip codes) with more borrowers who had credit application rejections a decade before the crisis (in 1996) had more mortgage defaults in 2006 and 2007. Mian and Sufi also find that "prior to the default crisis, these subprime zip codes [had experienced] an unprecedented relative growth in mortgage credit." The expansion in mortgage credit in these neighborhoods was combined with declining income growth (relative to other areas) and an increase in securitization of subprime mortgages.

Taylor [9] blames "too easy" monetary policy decisions, and the resulting low interest rates between 2002 and 2004 for causing the monetary excess, which in turn led to the housing boom and its subsequent collapse. He compares the housing market boom that could have resulted in the U.S. economy if monetary policy had been conducted according to the historically followed Taylor rule—a rule that suggested much higher interest rates for the period—with the actual housing boom. Based on the comparison, there would have been almost no housing boom with the higher rates. No boom would have meant no subsequent bust. The author dismisses the popular hypothesis of an excess of world savings—a "savings glut"—that many use to justify the low interest rates in the economy, and shows that there was, in fact, a global savings shortage, not an excess. Also, comparing monetary policy in other countries with that in the United States, Taylor notices that the housing booms were largest in countries where deviations of the actual interest rates from those suggested by the Taylor rule were the largest.

There is a large literature that analyzes mortgage defaults. The analysis is important for understanding the subprime mortgage crisis, which was triggered by a massive wave of mortgage delinquencies and foreclosures. Important contributions to this literature include Deng [10], Ambrose and Capone [11], Deng et al. [12], Calhoun and Deng [13], Pennington-Cross [14], Deng et al. [15], Clapp et al. [16], and Pennington-Cross and Chomsisengphet [17].

1.2 The Subprime Crisis is Not Unique

Demyanyk and Van Hemert [5] show evidence that the subprime mortgage crisis in the United States seems, in many respects, to have followed the classic lending boom-and-bust cycle documented by Dell'Ariccia et al. [18]. First, a sizeable boom occurred in the subprime mortgage market. Depending on the definition of "subprime," the market grew from three to seven times larger between 1998 and 2005 (see Mayer and Pence [19] for measures of the size and the increase of the subprime mortgage market based on U.S. Department of Housing and Urban Development and LoanPerformance definitions). Second, a definitive collapse of the market occurred in 2007, which was reflected in high delinquency, foreclosure, and default rates. A year later, the subprime mortgage crisis spilled over into other credit markets, creating a much larger financial crisis and global credit crunch. Third, the periods preceding the collapse were associated with loosening of underwriting standards, deteriorating loan quality, and increasing loan riskiness that were not backed up by an increasing price of this extra risk. In fact, the subprime-prime spread was actually declining over the boom period.

Increasing riskiness in the market, together with the decreasing price of this risk, leads to an unsustainable situation, which in turn leads to a market collapse. The subprime episode fits into this boom-bust framework easily. Moreover, not only have Demyanyk and Van Hemert [5] shown that the crisis followed a classic path known to policymakers and researchers in several countries but they have also shown that analysts could have foreseen the crisis as early as late 2005. It is not clear, though, whether the crisis could have been prevented at that point. Comparing the findings of Dell'Ariccia et al. [18] and Demyanyk and Van Hemert [5], it appears the United States (in 2007); Argentina (in 1980); Chile (in 1982); Sweden, Norway, and Finland in (1992); Mexico (in 1994); and Thailand, Indonesia, and Korea (in 1997) all experienced the culmination of similar (lending) boom-bust scenarios, but in very different economic circumstances.

Reinhart and Rogoff [20], who analyzed macro indicators in the United States preceding the financial crisis of 2008 and 18 other post-World War II banking crises in industrial countries, also found striking similarities among all of them. In particular, the countries experiencing the crises seem to share a similarity in the significant increases in housing prices before the financial crises commenced. Even more striking is evidence that the United States had a much higher growth rate in its house prices than the so-called Big Five countries in their crises (Spain in 1977, Norway in 1987, Finland in 1991, Sweden in 1991, and Japan in 1992). In comparing the real rates of growth in equity market price indexes, the authors again find that pre-crisis similarities are evident among all the crisis countries. Also, in comparing the current account as a percentage of gross domestic product (GDP), not only are there similarities between countries, but the United States had larger deficits than those of the other countries before their crises, reaching more than six percent of GDP. The authors noted, however, that there are great uncertainty associated with the still ongoing 2008-2009 crisis in the United States; therefore, it is not possible to project the path of crisis resolution based on the experiences of other countries.

1.3 Selected analyses of bank failure prediction

Demirguc-Kunt and Detragiache [21] study the determinants of the probability of a banking crisis around the world in 1980-1994 using a multivariate Logit model. They find that bank crises are more likely in countries with low GDP growth, high real interest rates, high inflation rates, and explicit deposit insurance system. Countries that are more susceptible to balance of payments crises also have a higher probability of experiencing banking crises.

Demirguc-Kunt and Detragiache [22] specifically investigate the relation between the explicit deposit insurance and stability in banking sector across countries. The authors confirm and strengthen the findings of Demirguc-Kunt and Detragiache [21] that explicit deposit insurance can harm bank stability. This happens because banks may be encouraged by the insurance to finance high-risk and high-return projects, which in turn can lead to more bank losses and failures. The authors find that deposit insurance has a more negative impact on the stability of banks in countries where the institutional environment is weak, where the coverage offered to depositors is more intensive, and where the scheme is run by the government rather than by the private sector.

Demirguc-Kunt et al. [23] examine what happens to the structure of the banking sector following a bank crisis. The authors find that individuals and companies leave weaker banks and deposit their funds in stronger banks; at the same time, the aggregate bank deposits relative to countries' GDP do not significantly decline. Total aggregate credit declines in countries after banking crises, and banks tend to reallocate their asset portfolios away from loans and improve their cost efficiency.

Wheelock and Wilson [24] analyze what factors predict bank failure in the United States, particularly. The authors use competing-risks hazard models with time-varying covariates. They find that banks with lower capitalization, higher ratios of loans to assets, poor quality loan portfolios and lower earnings have higher risk of failure. Banks located in states where branching is permitted are less likely to fail. This may indicate that an ability to create a branch network, and an associated ability to diversify, reduces banks' susceptibility to failure. Further, the more efficiently a bank operates, the less likely the bank is to fail.

Berger and DeYoung [25] analyze instances when U.S. commercial banks face increases in the proportion of nonperforming loans and reductions in cost efficiency between 1985 and 1994. The authors find that these instances are interrelated and Granger-cause each other.

1.4 Remedies for Financial Crises

Caprio et al. [26] indicate that recent financial crises often occur because of booms in macroeconomic sectors; the crises are revealed following "identifiable shocks" that end the booms. Importantly, the underlying distortions of economic markets build up for a long time before the crisis is identified (Demyanyk and Van Hemert [5] identify such a process for the U.S. subprime mortgage crisis). Caprio et al. [26] discuss the role of financial deregulation in predicting crises and identify a mechanism for interaction between the governments and regulated institutions. The authors propose a series of reforms that could prevent future crises, such as lending reform, rating agency reform and securitization reform. Most importantly, according to the authors, regulation and supervision should be re-strengthened to prevent such crises in the future.

In his research, Hunter [27] attempts to understand the causes of, and solutions for, the financial crises. He defines the beginning of the recent crisis in the United States to be the point in time when inter-bank lending stopped in the Federal Funds Market. Following this definition, the U.S. crisis began around October 8, 2008, when the Federal Funds Rate hit a high of seven percent during intraday trading. According to Hunter, the primary reason for trading halt was that banks were unsure about the exposure of their counterparties to MBS risk: "If a bank has a large share of its asset portfolio devoted to MBS, then selling MBS to get operating cash is infeasible when the price of MBS has declined significantly. Banks in this situation are on the brink of insolvency and may indeed have difficulty repaying loans they receive through the Federal Funds Market." The author suggests several solutions to the crisis. Among them, he emphasizes the importance of transparency in the operation of and analysis by MBS insurers and bond rating agencies. He also stresses the development of a systematic way of evaluating counterparty risk within the financial system. In the short term, he suggests that the Fed could encourage more borrowing through the Discount Window.

Diamond and Rajan [28] also analyze the causes of the recent U.S. financial crisis and provide some remedies for it. According to the authors, the first reason for the crisis was a misallocation of investment, which occurred because of the mismatch between the soft information loan officers based credit decisions on and the hard information (like credit scores) the securities trading agencies used to rate mortgage bonds. This was not a big problem as long as house prices kept rising. However, when house prices began to decline and defaults started increasing, the valuation of securities based on loans became a big problem (as the ratings may not truly capture the risk of loans within those securities). The second reason for the crisis was excessive holdings of these securities by banks, which is associated with an increased default risk. To solve or mitigate the crisis, Diamond and Rajan first suggest that the authorities can offer to buy illiquid assets through auctions and house them in a federal entity. The government should also ensure the stability of the financial system by recapitalizing those banks that have a realistic possibility of survival, and merging or closing those that do not.

Brunnermeier [29] tries to explain the economic mechanisms that caused the housing bubble and the turmoil in the financial markets. According to the author, there are three factors that led to the housing expansion. The first is a low interest-rate and mortgage-rate environment for a relatively long time in the United States, likely resulting from large capital inflows from abroad (especially from Asian countries) and accompanied by the lax interest rate policy of the Federal Reserve. Second, the Federal Reserve did not move to prevent the buildup of the housing bubble, most likely because it feared a possible deflationary period following the bursting of the Internet stock bubble. Third, and most importantly, the U.S. banking system had been transformed from a traditional relationship banking model, in which banks issue loans and hold them until they are repaid, to an "originate-to-distribute" banking model, in which loans are pooled, tranched and then sold via securitization. This transformation can reduce banks' monitoring incentives and increase their possibility of if they hold a large amount of such securities without fully understanding the associated credit risk.

Brunnermeier further identifies several economic mechanisms through which the mortgage crisis was amplified into a broader financial crisis. All of the mechanisms begin with the drop in house prices, which eroded the capital of financial institutions. At the same time, lenders tightened lending standards and margins, which caused fire sales, further pushing down prices and tightening credit supplies. When banks became concerned about their ability to access capital markets, they began to hoard funds. Consequently, with the drop in balance sheet capital and difficulties in accessing additional funding, banks that held large amounts of MBS failed (e.g., Bear Stearns, Lehman Brothers, and Washington Mutual), causing a sudden shock to the financial market.

Several researchers conclude that the ongoing crisis does not reflect a failure of free markets, but a rather reaction of market participants to distorted incentives (Demirguc-Kunt and Serven [30]). Demirguc-Kunt and Serven argue that the "sacred cows" of financial and macro policies are not "dead" because of the crisis. Managing a systemic panic requires policy decisions to be made in different stages: the immediate containment stage and a longer-term resolution accompanied by structural reforms. Policies employed to reestablish confidence in the short term, such as providing blanket guarantees or government buying large stakes in the financial sector, are fraught with moral hazard problems in the long term and might be interpreted as permanent deviations from well-established policy positions by the market. The long-term financial sector policies should align private incentives with public interest without taxing or subsidizing private risk-taking (Demirguc-Kunt and Serven [30]). Although well designed prudential regulations cannot completely eliminate the risk of crises, they can make crises less frequent. However, balancing the short- and long-term policies becomes complex in the framework of an integrated and globalized financial system.

Analyzing the Asian financial crisis, Johnson et al. [31] present evidence that country-level corporate governance practices and institutions, such as the legal environment, have an important effect on currency depreciations and stock market declines during financial crisis periods. The authors borrow from the corporate governance literature (see Shleifer and Vishny [32]) theoretical arguments that corporate governance is an effective mechanism to minimize agency conflicts between inside managers and outside stakeholders. The authors empirically show that corporate governance—measured as efficiency of the legal system, corruption and rule of law—explains more of the variation in exchange rates and stock market performance than do macroeconomic variables during the Asian crisis.

Angkinand [33] reviews methods used to evaluate the output loss from financial crises. The author argues that an empirical methodology estimating the total output loss per crisis from the deviation of actual output from the potential output trend—the gap approach—estimates the economic costs of crises better than a methodology that estimates a dummy variable to capture the crisis—the dummy variable approach— because the output costs of different crisis episodes vary significantly.

A book by Barth et al. [34] provides a descriptive analysis explaining how the crisis emerged in the United States and what actions the U.S. government is taking to remedy the economic and credit market contractions. A valuable contribution of the study is a list of U.S. bailout allocations and obligations. This list is also frequently updated and reported on the Milken Institute web page.[6]

2 Review of Operations Research Models

In this section, we describe selected operations research models that are frequently used in the empirical literature to predict defaults or failures of banks and that could be used to predict defaults of loans or non-financial institutions.

Predicting the default risk for banks, loans and securities is a classic, yet timely issue. Since the work of Altman [35], who suggested using the so-called "Z score" to predict firms' default risk, hundreds of research articles have studied this issue (for reference, see two review articles: Kumar and Ravi [36] and Fethi and Pasiouras [37]).

Several studies have shown that intelligence modeling techniques used in operations research can be applied for predicting the bank failures and crises. For example, Celik and Karatepe [38] find that artificial neural network models can be used to forecast the rates of non-performing loans relative to total loans, capital relative to assets, profit relative to assets, and equity relative to assets. In another example, Alam et al. [39] demonstrate that fuzzy clustering and self-organizing neural networks provide classification tools for identifying potentially failing banks.

Most central banks have employed various Early Warning Systems (EWS) to monitor the risk of banks for years. However, the repeated occurrence of banking crises during the past two decades—such as the Asian crisis, the Russian bank crisis, and the Brazilian bank crisis—indicates that safeguarding the banking system is no easy task. According to the Federal Deposit Insurance

[6] http://www.milkeninstitute.org/publications/ publications.taf?function=detail&ID=38801185&cat=resrep.

Corporation Improvement Act of 1991, regulators in the United States must conduct on-site examinations of bank risk every 12–18 months. Regulators use a rating system (the CAMELS rating) to indicate the safety and soundness of banks. CAMELS ratings include six parts: capital adequacy, asset quality, management expertise, earnings strength, liquidity and sensitivity to market risk.

Davis and Karim [40] evaluate statistical and intelligence techniques in their analysis of the banking crises. Specifically, they compare the logistic regression (Logit) and the Signal Extraction EWS methods.[7] They find that the choice of estimation models makes a difference in terms of indicator performance and crisis prediction. Specifically, Logit model performs better as a global EWS and Signal Extraction is preferable as a country-specific EWS. Davis and Karim [41] test whether EWS based on the Logit and binomial tree approaches (this technique is described below) could have helped predicting current subprime crisis in the US and UK. Using twelve macroeconomic, financial and institutional variables, they find that among global EWS for the US and UK, the Logit performs the best. However, this model as many others has only a small ability to predict the crises.

West [42] uses the Logit model, along with factor analysis, to measure and describe banks' financial and operating characteristics. Data was taken from Call and Income Reports, as well as Examination Reports for 1,900 commercial banks in several states of the U.S. According to the analysis, the factors identified by the Logit model as important descriptive variables for the banks' operations are similar to those used for CAMELS ratings. He demonstrates that his combined method of factor analysis and Logit estimation is useful when evaluating banks' operating conditions.

Among the statistical techniques analyzing and predicting bank failures, Discriminant Analysis (DA) was the leading technique for many years (e.g., Karels and Prakash [43], Haslem et al. [44]). There are three subcategories of DA: Linear, Multivariate, and Quadratic. One drawback of DA is that it requires a normal distribution of regressors.[8] When regressors are not normally distributed,

[7]The term "signal extraction" refers to a statistical tool that allows for isolation of a pattern of the data—the signal—out of noisy or raw time-series data.

[8]Martin [45] is an early study that uses both Logit and DA statistical methods to predict bank failures in the period from 1975 to 1976, based on data obtained from the Federal Reserve System. The author finds that the two models have similar classifications in terms of identifying failures/non-failures of banks.

maximum likelihood methods, such as Logit, can be used.[9] DA is a tool for analyzing cross-sectional data. If one needs to analyze time series data on bank firm, or loan defaults, hazard or duration analysis models can be used instead of DA models.[10]

Canbas et al. [51] propose an Integrated Early Warning System (IEWS) that combines DA, Logit, Probit, and Principal Component Analysis (PCA), which can help predict bank failure. First, they use PCA to detect three financial components that significantly explain the changes in the financial condition of banks. They then employed DA, Logit and Probit regression models. By combining all these together, they construct an IEWS. The authors use the data for 40 privately owned Turkish commercial banks to test the predictive power of the IEWS, concluding that the IEWS has more predictive ability than the other models used in the literature.

Among intelligence techniques, Neural Networks (NN) is the most widely used. The NN model have developed out of the fields of artificial intelligence and brain modeling, and contains mathematical and algorithmic elements that mimic the biological neural networks of the human nervous system. The method considers an interrelated group of artificial neurons and processes information associated with them using a so-called connectionist approach, where network units are connected by a flow of information. The structure of NN models changes based upon external or internal information that flows through the network during the learning phase and uses nonlinear function approximation tools to test the relationship between explanatory factors.

Boyacioglu et al. [2] compare various NN, Support Vector Machine (SVM) and multivariate statistical methods to the bank failure prediction problem in Turkey. They use similar financial ratios as those used in CAMELS ratings. In the category of NN, four different architectures are employed, namely MLP, CL, SOM and LVQ (the details of these architectures are not described in this review). The multivariate statistical methods tested are multivariate discriminant analysis, K-means cluster analysis, and Logit regression analysis. According to the comparison, MLP and LVQ can be considered the most successful models in predicting the financial failure of banks in the sample.

[9] As in, for example, Martin [45], Ohlson [46], Kolari et al. [47], and Demyanyk [6].
[10] See Cole and Gunther [48], Lane et al. [49], Molina [50], among many others.

The Back-Propagation Neural Networks (BPNN) model is a multilayer NN model. The first layer is constructed from input units, the middle layer consists of hidden units, and the last layer consists of output units. Each upper layer receives inputs from units of a lower level and transmits output to units of the layer above it. The important feature of BPNN is that the errors generated by units of a hidden layer are calculated by back-propagating the errors of the output sent by levels of its corresponding layer. BPNN overcomes the classification restriction of a single-layer network, and it is one of the most commonly used methods for classification and prediction problems. Many studies compare the classification and prediction accuracy between BPNN and other methods and find that, in most cases, BPNN outperforms other models.

For example, Tam [52] uses a BPNN model to predict bank failures in a sample of Texas banks one year and two years prior to their failures. The input variables he uses are bases on the CAMELS criteria. He finds that BPNN outperforms all other methods, such as DA, Logit, and K-nearest neighbor (this method is described below) in terms of their predictive accuracy. Similarly, several other studies, briefly described below, find that BPNN offers a better prediction or a better classification accuracy than other methods.

Ravi and Pramodh [53] propose a Principal Component Neural Network (PCNN) architecture for bankruptcy prediction in commercial banks. In this architecture, the hidden layer is completely replaced by what is referred to as a "principal component layer." This layer consists of a few selected components that perform the function of hidden nodes. The authors tested the framework on a data from Spanish and Turkish banks. According to the estimated results, hybrid models that combine PCNN and several other models predict banking bankruptcy outperform other classifiers used in the literature.

Tam and Kiang [54] compare the power of linear discriminant analysis (LDA), Logit, K-Nearest Neighbor (described below), Interactive Dichotomizer 3 (ID3), feedforward NN and BPNN on bank failure prediction problems. They find that BPNN outperforms the other techniques for a one-year-prior training sample, while DA outperforms the others for a two-years-prior training sample. However, for holdout samples, BPNN outperforms the others in both the one-year-prior and the two-years-prior samples. In the jackknife method, BPNN also outperforms others in both the one-year-prior and the two-years-prior holdout samples. In all, they conclude that NN outperforms the DA method.

Bell [55] compares Logit and BPNN models in predicting bank failures. In his study, he uses 28 candidates for predictor variables. The architecture of BPNN has twelve input nodes, six hidden nodes and one output node. He finds that neither the Logit nor the BPNN model dominates the other in terms of predictive ability. However, BPNN is found to be better for complex decision processes.

Swicegood and Clark [56] compare DA, BPNN and human judgment in predicting bank failures. The authors use data from bank Call Reports. They find that BPNN outperforms other models in identifying underperforming banks.

Olmeda and Fernandez [57] compare the accuracy of bankruptcy prediction methods that include classifiers in a stand-alone model with those in a hybrid system, which integrates several classifiers. They propose a framework for formulating the optimal mixture of the technologies as an optimization problem and solve it using a genetic algorithm. Using data from the Spanish banking system, they find BPNN performs the best, Logit the second best, and multivariate adaptive splines (MARS), C4.5 (not described in this review) and DA follow in that order. The authors then combine models using a voting scheme and a compensation aggregation method. They find that the prediction rates produced by the combined models are higher than those produced by the stand-alone model.

The Trait Recognition technique develops a model from different segments of the distribution of each variable and the interactions of these segments with one or more other variables' segmented distributions. It uses two sets of discriminators, the "safe traits" and the "unsafe traits," known as features. These features can then be used to predict bank failures by voting each bank and classifying it as "failed" or "non-failed." Trait recognition is a nonparametric approach that does not impose any distributional assumptions on the testing variables already contained within the data. The advantage of the trait recognition approach is that it exploits information about the complex interrelations of variables. The power of this approach depends on the adequate selection of cut points for each of the variables, so that all failed banks can be located below some threshold and all non-failed banks above it.

Kolari et al. [47] develop an EWS based on Logit and the Trait Recognition method for large U.S. banks. The Logit model correctly classifies over 96% of the banks one year prior to failure and 95% of the banks two years prior to failure. For the Trait Recognition model, half of the original sample is used. They find that with data classification both one year and two years prior to failure, the accuracy of the Trait Recognition model is 100%. Therefore, they conclude that the Trait Recognition model outperforms the Logit model in terms of type-I and type-II errors.

Lanine and Vander Vennet [58] employ a Logit model and a Trait Recognition approach to predict failures among Russian commercial banks. The authors test the predictive power of the two models based on their prediction accuracy using holdout samples. Although both models perform better than the benchmark, the Trait Recognition approach outperforms Logit in both the original and the holdout samples. For the predictable variables, they find that expected liquidity plays an important role in bank failure prediction, as well as asset quality and capital adequacy.

The Support Vector Machine (SVM) technique is based on the Structural Risk Minimization (SRM) principle from computational learning theory, which was introduced by Vapnik [59]. In the SVM method, input data is structured as two sets of vectors in a multi-dimensional space. The purpose is to maximize the margin between the two data sets. In order to calculate the margin, two parallel hyperplanes need to be constructed, one on each side of the separating hyperplane, which are forced against the two data sets. A good separation can be achieved by the hyperplane that has the largest distance from the neighboring data points of both classes; the larger the margin, the better the generalization error of the classifier. In sum, SVM uses a special linear model and the optimal separating hyperplane to achieve the maximum separation between two classes. The training points that are closest to the maximum margin hyperplane are called support vectors. Such models are utilized in Vapnik [59], Boyacioglu et al. [2], Chen and Shih [1] and Huang et al. [60], among others.

The Decision Tree (DT) technique, which comes from research on machine learning, uses a recursive partitioning algorithm to institute rules on a given data set. Most decision tree algorithms are used for solving classification problems. However, algorithms like classification and regression trees (CART) can also be used for solving prediction problems. In this case, a binary decision tree needs to be developed through a set of IF-THEN rules. These rules can be used to accurately classify cases (e.g., banks). A number of algorithms are used for building decision trees, including CHAID (chi-squared automatic interaction detection), CART, C4.5 and C5.0. For more information, see Marais et al. [61] and Frydman et al. [62]

The Rough Set technique is a mathematical method for modeling incomplete data based on a concept given by Pawlak [63]. It uses an approximation of the usually vague objective into a predefined categories, which then can be iteratively analyzed. See Greco et al. [64] for details.

Case-Based Reasoning (CBR) is a method similar to the cognitive process humans follow in solving problems intuitively. CBR can be represented by a schematic cycle comprising four steps. The first step is to retrieve the most similar cases. The second is to reuse the cases to attempt to solve the problem. The third is to revise the proposed solution, if necessary. And the fourth is to retain the new solution as a part of a new case. CBR methodology enables an analyst to predict failure of a company based on failures of other companies that occurred in the past.

The Nearest Neighbor technique classifies an object in the class of its nearest neighbor in the measurement space, using a certain distance measure such as local metrics, global metrics, or Mahalanobis or Euclidean distance. The method has a variety of applications, ranging from analyzing settlement and patterns in landscape, spam classification, or any other distribution of objects and events. One can determine if objects or events are random, clustered, or distributed regularly. The K-nearest neighbor (K-NN) is a modified Nearest Neighbor technique. In this model, K is a positive, usually small, integer. An object (for example, a bank) is assigned to the class most common amongst its K nearest neighbors (the class is either "failed" or "non-failed").

Zhao et al. [65] compare the performance of several factors that are used for predicting bank failures based on Logit, DT, NN, and K-NN models. The authors find that a model choice is important in terms of explanatory power of predictors.

The Soft Computing technique is a hybrid system combining intelligence and statistical techniques. Specifically, it refers to a combination of computational techniques in order to model and analyze complex phenomena. Compared to traditional “hard” computing techniques—which use exact computations and algorithms—soft computing is based on *inexact* computation, trial-and-error reasoning, and subjective decision making. Such computation builds on mathematical formalization of the cognitive processes similar to those of human minds. More information is available in Back and Sere [66], Jo and Han [67], Tung et al. [68].

Data Envelopment Analysis (DEA) is a non-parametric performance method used to measure the relative efficiencies of organizational or decision-making units (DMUs). DEA applies linear programming to observing inputs consumed and outputs produced by decision-making units (such as branches of a bank or departments of an institution). It constructs an efficient production frontier based on best observed practices. Each DMU's efficiency is then measured against this computed frontier. The relative efficiency is calculated by obtaining the ratio of the weighted sum of all outputs and the weighted sum of all inputs. The weights are selected to achieve Pareto optimality for each DMU.

Luo [69] uses the DEA model to evaluate profitability and marketability efficiencies of large banks. In the model, the author analyzes banks' revenue and profit as the measured outputs of both efficiencies. He finds that marketability inefficiency creates more problems for the analyzed banks than profitability inefficiency. In an application to prediction of banking crises, the findings suggest that overall technical efficiency of the profitability performance is associated with a likelihood of bank failure.

Avkiran [70] analyzes the profit efficiency of commercial banks in the United Arab Emirates by applying a standard DEA and a network DEA (NDEA) technique. The author mentions that the standard DEA does not provide sufficient details to identify the specific sources of inefficiency; network DEA gives access to this underlying diagnostic information, because each division of an institution can be treated as an independent DMU under the NDEA. Note that the efficiency measures derived from stochastic DEA do not account for statistical noise; the impact of measurement error on efficiency is generally overlooked and it is not possible to conduct a formal statistical inference by using stochastic DEA.

Kao and Liu [71] formulate a DEA model of interval data for use in evaluating the performance of banks. Their study makes advance predictions of the performance of 24 Taiwan banks based on uncertain financial data (reported in ranges) and also presents the prediction of efficiency scores (again in ranges). They find that the model-predicted efficiency scores are similar to the actual (calculated from the data) efficiency scores. They also show that the poor performances of the two banks taken over by the Financial Restructuring Fund of Taiwan could actually have been predicted in advance using their method.

Tsionas and Papadakis [72] provide a statistical framework that can be used with stochastic DEA. In order to make inference on the efficiency scores, the authors use a Bayesian approach to the problem set up around simulation techniques. They also test the new methods on the efficiency of Greek banks, and find that the majority of the Greek banks operate close to market best-practices.

Cielen et al. [73] compare the performance of a DEA model, Minimized Sum of Deviations (MSD), and a rule induction (C5.0) model in bankruptcy prediction. MSD is a combination of linear programming (LP) and DA. Using data from the National Bank of Belgium, they find that MSD, DEA and C5.0 obtain the correct classification rates of failure for 78.9%, 86.4% and 85.5% of banks, respectively. They conclude that DEA outperformed the C5.0 and MSD models in terms of accuracy.

Kosmidou and Zopounidis [74] develop a bank failure prediction model based on a multicriteria decision technique called UTilites Additives DIScriminants (UTADIS). The purpose of UTADIS method is to develop a classification model through an additive value function. Based on the values obtained from the additive value function, the authors classify banks into multiple groups by comparing them with some reference profiles (also called cut-off points). UTADIS is well suited to the ordinal classification problems and it is not sensitive to the statistical problems because the additive utility function is performed through mathematical linear programming techniques instead of statistical methods. Using a sample of U.S. banks for the years 1993-2003, the authors use this technique to differentiate U.S. banks between failed and non-failed. The results show that UTADIS is quite efficient for the evaluation of bank failure as early as four years before it occurs. The authors also compare UTADIS with other traditional multivariate data analysis techniques and find that UTADIS performs better, and could be used efficiently for predicting bank failures.

The Multicriteria Decision Aid (MCDA) method is a model that allows for the analysis of several preference criteria simultaneously. Zopounidis and Doumpos [75] apply MCDA to sorting problems, where a set of alternative actions is classified into several predefined classes. Based on the multidimensional nature of financial risk, Doumpos and Zopounidis [76] propose a new operational approach called the Multi-Group Hierarchical Discrimination (M.H.DIS) method—which originates from MCDA—to determine the risk classes to which the alternatives belong. Using World Bank data, the authors apply this method to develop a model which classifies 143 countries into four risk classes based on their economic performance and creditworthiness. The authors conclude that this method performs better than traditional multiple discriminant analysis.[11]

MCDA is can be used in credit ratings and bank soundness. For example, Gaganis et al. [77] apply a MCDA model using the UTADIS method to classify banks into three groups based on their soundness. The sample includes 894 banks from 79 countries, and the model is developed through a tenfold cross-validation procedure. Their results show that asset quality, capitalization and the market where banks operate are the most important criteria in classifying the soundness of banks. Profitability and efficiency are also important factors associated with banks performance. Furthermore, they find that UTADIS outperforms DA and Logit in terms of classification accuracies. Zopounidis and Doumpos [78] also explore if the UTADIS methods are applicable for analyzing business failure. They compare this method to DA and standard Logit and Probit statistical models.

Pasiouras et al. [79] test whether MCDA model can be used to replicate the credit rating of

[11] There are several other models, not discussed in this section, such as Fuzzy Logic (FL) techniques, Evolutionary Approach, and others.

Fitch on Asian banks. Five financial and five non-financial variables measuring bank and country characteristics are included in the model, and the model is tested through a tenfold cross-validation. The results show that "equity/customer and short-term funding, net interest margin and return on average equity, are the most important financial variables. The number of shareholders, the number of subsidiaries and the banking environment of the country" are the most important non-financial factors. The authors compare the accuracy of this prediction model with that of DA and ordered Logit; they find that MCDA is more efficient and that it replicates the Fitch credit ratings with the "satisfactory accuracy."

Niemira and Saaty [80] use a multiple criteria decision-making model to predict the likelihood of a financial crisis based on an Analytic Network Process (ANP) framework. They test the model for the US bank crisis during 1990s, and find that the ANP analysis provides a structure that can reduce judgmental forecast error through improved reliability of information processing. They conclude that the ANP framework is more flexible and is more comprehensive than traditional models, and it is a promising methodology to forecast the probability of crises.

Ng et al. [81] propose a Fuzzy Cerebellar Model Articulation Controller model (FCMAC) based on a compositional rule of inference called FCMAC-CRI(S). The new architecture integrates fuzzy systems and NN to create a hybrid structure called neural fuzzy networks. This new network operates through localized learning. It takes as inputs data from public financial information and analyzes patterns of financial distress through fuzzy IF-THEN rules. Such processing can provide a basis for an EWS and insights for various aspects of financial distress. The authors compare the accuracy of FCMAC-CRI(S) to Cox's proportional hazard model and the GenSoFNN-CRI(S) network model and find that the performance of the new approach is better than that of the benchmark models.

3 Concluding remarks

This article summarizes empirical economics and operations research articles that aim to explain, predict, and remedy financial crises and bank failures in the United States and other countries. The paper provides an analysis of financial and economic circumstances associated with the subprime mortgage crisis in the United States along with an extensive review of intelligence techniques used in the operations research literature to predict bank failures. We suggest that operations research techniques be more broadly applied in analyses of financial crises.

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