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In this article 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. We suggest that the level of cross-border holdings of long-term securities between the United States and the rest of the world may indicate a direct link between the turmoil in the securitized market originated in the United States and that in other countries. 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 extensively outline the methodologies used in them. The intent of this article is to promote future empirical research for preventing financial crises.

Key words: subprime, crisis, mortgage, bank failure, operations research.

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

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Introduction

This article analyzes financial and economic circumstances associated with the global financial turmoil that has led to severe crises in many countries. 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 market as subprime 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.

The subprime 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.[1]

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),[2] it is useful to compare it with the value of the entire mortgage debt in the United States (approximately $11.3 trillion)[3] and the value of securitized mortgage debt ($6.8 trillion).[4] 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 relatively small size as the U.S. subprime market could not cause

[1] See Demyanyk and Van Hemert [1] and Demyanyk [2] for a more detailed description and discussion.
[2] As the total value of subprime securities issued between 2000 and 2007, calculated by Inside Mortgage Finance, 2008.
[3] Total value of mortgages outstanding in 2Q 2008. Source: Inside Mortgage Finance, 2008
[4] Total value of mortgage securities outstanding in 2Q 2008. Source: Inside Mortgage Finance, 2008

significant problems to wider boundaries 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 credit crunch.

The structure of the paper is as follows. Section 1 analyzes the collapse of the subprime mortgage market in the United States and outlines factors associated with it. Section 2 links cross-border security holdings with cross-border subprime crisis spill-overs. Section 3 outlines similarities between the financial and banking crises in the United States and those in other countries. Section 4 summarizes suggestions of research economists about how to remedy the current crisis and possibly avoid crises in the future. Section 5 summarizes empirical methodologies used in the Economics and Operations Research studies analyzing and predicting bankruptcies and defaults. Section 6 concludes.

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 to and exit from the distressed mortgage market (uncertainty froze the market; a limited number of home sales/purchases occurred), and overall economic slowdown created a vicious circle—a self-sustaining loop—an exit from which was beyond the capacity of market forces to find.

Demyanyk and Van Hemert [1] 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, 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 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 [2] empirically showed that subprime mortgages were, in fact, a temporary phenomenon, i.e., borrowers who took subprime loans seemed to have used mortgages as bridge (temporary) 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 consecutive defaults. For example, Keys et al. [3] 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 [4] show that securitization is associated with increased subprime lending and subsequent defaults. More specifically, the authors show that geographical areas (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 [5] 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.

2 Cross-border Security Holdings and Cross-border Crisis

2.1 Data

We briefly analyze the data, provided by the Treasury International Capital System,[5] covering cross-border holdings of long-term securities. The securities holdings are measured at market value, based on information reported separately for each security by custodians, issuers, and investors. Annual data are available for foreign holdings of U.S. securities and U.S. holdings of foreign securities. These data are considered highly reliable. In their article, Bertaut et al. [6] provide a detailed explanation of the data and outline several possible applications of it.

We also refer to the data for U.S. Mortgage Backed Securities (MBS) from several Inside Mortgage Finance publications: Mortgage Market Statistical Annual (2008) and Mortgage Yearbook for First Half 2008.

2.2 Descriptive analysis

The world experienced several dimensions of a securitization boom in the precrisis years. Each of these dimensions, described below in greater detail, has a domestic and an international component.

Along one dimension, the United States experienced a remarkable increase in mortgage securitization in the last decade. The total outstanding volume of MBS increased from approximately one trillion dollars in 1990 to almost seven trillion dollars by the second quarter of 2008. Non-agency MBS outstanding increased from 55 billion to two trillion dollars during the same time period. Mortgage loans for these mortgage securities were originated, pooled and securitized in the United States and then sold domestically and abroad. As a relatively new phenomenon, subprime mortgage securitization created an additional boom. Only 11 billion USD worth of subprime securities were originated in 1994; this number reached 432 billion by 2007 (one-third of all mortgage securities originated in 2007). A very large portion of all mortgages in the United States went into the mortgage securitized market: between 1994 and 2007, the portion of all mortgages that

[5] The data are available at http://www.treas.gov/tic.

was securitized ranged from 50 to 75 percent, while the portion of subprime mortgages that was securitized ranged from 31 percent in 1994 to 93 percent in 2007.

Following another dimension, foreign holdings of U.S. securities increased dramatically in the pre-crisis decade (between 1995 and 2005). Foreign countries held between 40 and 70 percent more U.S. securities than the United States held foreign securities (from the rest of the world). Comparing only holdings of long-term debt securities, foreign holdings of U.S. securities were approximately six trillion USD in 2007, while United States held only 1.6 trillion USD worth of foreign securities. Total foreign holdings of U.S. long-term debt securities were increasing by one to two trillion USD each year since 2003.

The United States started showing the first signs of a severe subprime mortgage crisis in 2007. Just one year after origination, on average across loan contract and borrowers types, about 20 percent of subprime securitized mortgages originated in 2006 either had defaulted or were about to default on their contracts.[6] After that, the default rates were increasing monotonically by loan age, i.e., more and more defaults (foreclosures) were occurring with time for many months. These mortgage loans are parts of subprime securities, which were sold to domestic and international investors. The international dimension is responsible for the first cross-border spill-overs of the subprime mortgage crisis. In other words, cross-border holdings of (subprime) securities—those that triggered the U.S. subprime crisis—and the cross-border financial crisis are interconnected.

3 The Subprime Crisis is Not Unique

Demyanyk and Van Hemert [1] show evidence that the subprime mortgage crisis in the United States seemed, in many respects, to follow the classic lending boom-and-bust cycle documented by Dell'Ariccia et al. [7]. 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 [8] for measures of the size and the increase of the

[6] More information about default rates for different loan ages and origination years is available in Demyanyk and Van Hemert [1].

subprime mortgage market based on U.S. Department of Housing and Urban Development and LoanPerformance definitions). Second, a definite bust (collapse) of the market occurred in 2007, which was reflected in high delinquency, foreclosure, and default rates.

Moreover, a year later, the subprime mortgage crisis spilled over into 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; 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. Moreover, not only have Demyanyk and Van Hemert [1] shown that the crisis followed a classic path known to policymakers and researchers in several countries; they have also shown that analysts could have seen the crisis coming as early as late 2005. It is not clear, though, whether it could have been prevented. Comparing the findings of Dell'Ariccia et al. [7] and Demyanyk and Van Hemert [1], 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 [9], 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 similarities 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, comparing the current account as a percentage of gross domestic product (GDP), not only are there similarities, but the United States had deficits more severe than those of the other countries before their crises, reaching more than six percent of GDP. The authors noted, however, the 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.

4 Remedies for Financial Crises

Caprio et al. [10] 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 [1] identify such process for the U.S. subprime mortgage crisis). Caprio et al. [10] discuss a role of financial deregulation and the 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 [11] attempts to understand the causes of, and provide solutions to, the financial crises. He defines the beginning of the crisis in the United States as a circumstance where inter-bank lending stops in the Federal Funds Market. Following this definition, the U.S. crisis has started around October 8, 2008, when the Federal Funds Rate hit a high of seven percent in intraday trading. According to Hunter, the main reason for this 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 MBS insurers and bond rating agencies, and of having a systematic way of evaluating counterparty risk. In the short term, he suggests that the Fed should encourage more borrowing through the Discount Window.

Diamond and Rajan [12] analyze the reasons for the recent U.S. financial crisis and provide some remedies for it. According to the authors, the first reason for the crisis was misallocation of investment, which occurs when loan officers assess borrower creditworthiness based on soft information and rating agencies can only do so based on hard information, such as the credit score of the homeowner. 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 originated in this way became a big problem (as the ratings may not truly capture the risk of those securities). The second reason was excess holdings of these securities by banks; this is associated with an increased default risk for the banks. Diamond and Rajan also provide some suggestions to solve or mitigate the crisis. First, the authorities can offer to buy illiquid assets through auctions and house them in a federal entity. Second, the government should ensure the stability of the financial system. Government can recapitalize banks that have a realistic possibility of survival, and merge or close those that do not.

Brunnermeier [13] 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 main factors leading to the housing bubble. The first is a low interest-rate and mortgage-rate environment for a relatively long time in the United States; this environment most likely resulted from large capital inflows from abroad, especially from Asian countries, 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 in time, most likely because it feared a deflationary period after the bursting of the Internet bubble. Third, and most importantly, the U.S. banking system has 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 exposure to risk if they hold a large amount of such securities.

Brunnermeier further identifies several economic mechanisms through which the mortgage crisis was amplified into a severe financial crisis. All of the mechanisms begin with the drop of house prices, which erodes the capital of financial institutions. At the same time, lenders tighten lending standards and margins, which cause fire sales, further pushing down prices and tightening funding. When banks become concerned about their own access to capital markets, they start hoarding funds. Consequently, with the drop of balance sheet capital and difficulties in accessing additional funding, banks that hold large amount of MBS fail (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 reaction of market participants to distorted incentives (Demirguc-Kunt and Serven [14]). Demirguc-Kunt and Serven argue that the "sacred cows" of financial and macro policies are not dead. Managing a systemic crisis 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 owning large stakes in the financial sector, are fraught with moral hazard problems in the long term and should not be interpreted as permanent deviations from well-established policy positions. The long-term financial sector policies should align private incentives with public interest without taxing or subsidizing private risk-taking (Demirguc-Kunt and Serven [14]). 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. [15] present evidence that country-level corporate governance, such as legal protection environment, has an important effect on currency depreciations and stock market declines during financial crisis periods. The authors borrow from the corporate governance literature (see Deng [16]) theoretical arguments that corporate governance is an effective mechanism to minimize agency conflicts between inside managers and outside stakeholders. When the expected rate of return on investment falls, a shock to investor confidence will lead to increased expropriation by managers. Since investors would expect the expropriation, capital inflow will decrease and capital outflow will increase for a country. These effects usually lead to lower stock prices and depreciated exchange rates. The authors empirically test the above hypothesis and 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 [17] 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. [18] provides a descriptive analysis explaining how the crisis emerged in the United States and what the U.S. government is undertaking to remedy the economic and credit markets. 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.[7]

5 Review of Empirical Models Predicting Defaults

How to predict the default risk for banks, loans and securities is an important, old, but also timely, issue, given the current financial crisis. The section below describes empirical models used in predicting mortgage defaults and banking defaults in general. Most central banks have had various Early Warning System (EWS) to monitor the risk of banks for many years. However, the repeated occurrence of banking crises during 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. For the United States, according to the Federal Deposit Insurance Corporation Improvement Act of 1991, regulators 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

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

ratings include six parts: capital adequacy, asset quality, management expertise, earnings strength, liquidity and sensitivity to market risk.

Since the work of Altman [19], 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 [20] and Fethi and Pasiouras [21]). Models for predicting bank crises fall into two broad categories: statistical and intelligence techniques. Most models are based on balance sheet financial ratios.

5.1 Statistical methods

Among the statistical techniques analyzing and predicting bank failures, Discriminant Analysis (DA) was the leading technique for a long time (e.g., Karels and Prakash [22], Haslem et al. [23]). There are three subcategories of discriminant analysis: Linear, Multivariate, and Quadratic discriminant analyses. One drawback of DA is that it requires a normal distribution of regressors.

When regressors are not normally distributed, maximum likelihood methods, such as, for example, logistic regressions (logit), are used (for details on the application of such models, see Martin [24], Ohlson [25], Kolari et al. [26], and Demyanyk [2]). Logit and discriminant analysis are both cross-sectional methods. If one needs to analyze time series data on bank (firm, loan) defaults, hazard or duration analysis models can be used (e.g., Cole and Gunther [27], Lane et al. [28], Molina [29], and many more).

There is a large literature that analyzes mortgage terminations, either through prepayment or default. Important contributions to this literature include Deng [30], Ambrose and Capone [31], Deng et al. [32], Calhoun and Deng [33], Pennington-Cross [34], Deng et al. [35], Clapp and Deng [36], Pennington-Cross and Chomsisengphet [37], and Demyanyk and Van Hemert [1].

5.2 Intelligence techniques

In this section, we describe several intelligence techniques 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.

Among these intelligence techniques, *Neural Networks* (NN) is the most widely used model (see, for example, Chen and Shih [38] and Boyacioglu et al. [39]). NN models have developed from the field of artificial intelligence and brain modeling. It has elements of 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 connectionist approach. 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, neural networks have two advantages. The most important one is that neural networks 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 methodologies, however, are also able to deal with nonlinear relationships between factors in the data).

There are several types of neural networks, each with a different purpose, architecture and learning algorithm. Back-propagation neural networks (BPNN), multi-layer preceptron (MLP), radial basis function networks (RBFN), probabilistic neural networks (PNN), competitive learning neural networks (CLNN), self-organizing feature map (SOM), learning vector quantization (LVQ) and cascade correlation neural networks (Cascor) are some of the popular NN architectures.

The *Trait Recognition* technique is initially developed 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. Then these features can be used used, for example predicting bank failures, to vote on each bank and classify it as "failed" or "non-failed." Trait recognition is a nonparametric approach that does not impose any distributional assumptions on the testing variables. 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 are above that threshold. To read more about the model and its application, see, for example, Kolari et al. [26] and Lanine and Vander Vennet [40].

The *Support Vector Machine* (SVM) technique is based on the Structural Risk Minimization (SRM) principle from computational learning theory, which was introduced by Vapnik [41]. An SVM views input data as two sets of vectors in a multiple 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, e.g., Vapnik [41], Boyacioglu et al. [39], Chen and Shih [38] and Huang et al. [42].

The *Decision Tree* (DT) technique uses a recursive partitioning algorithm to induce rules on a given data set. It comes from research on machine learning. Most decision tree algorithms are used for solving classification problems. However, algorithms like CART (classification and regression trees) can also be used for solving prediction problems. In this case, a binary decision tree needs to be developed. This can be established through a set of IF-THEN rules. Then 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. [43] and Frydman et al. [44]

The *Rough Set* technique is a mathematical method for modeling incomplete data based on a concept given by Pawlak [45]. It uses an approximation of the (usually vague) objective into a predefined categories, which then can be iteratively analyzed. See Greco et al. [46] 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 case(s). The second is to reuse the case(s) 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. The advantage of CBR is its ability to give an explanation for its decision based on previous cases. Comprehensibility of the decision is often important in solving financial problems. When a company is identified as failing, CBR can give examples of similar companies that failed in the past as a justification for its prediction.

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 K-nearest neighbor (K-NN) is a modified Nearest Neighbor technique. In this model, K is a positive, usually small, integer. An object (i.e., a bank) is assigned to the class most common amongst its K nearest neighbors (the class is either "failed" or "non-failed"). For a further discussion, more detailed mechanism, and an application of the model, see Zhao et al. [47].

The *Soft Computing* technique is a hybrid system combining intelligence and statistical techniques. Specifically, it refers to a combination of seemingly unrelated computational techniques used to model and analyze very complex phenomena. Unlike traditional hard computing techniques which focus on exactness, certainty and rigor, soft computing is based on *inexact* computation, heuristic 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 [48], Jo and Han [49], Tung et al. [50].

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. It constructs an efficient production frontier based on best observed practices. Each DMU's efficiency is then measured relative to 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.

The *Multicriteria Decision Aid* (MCDA) method is a model that allows for the analysis of several preference criteria simultaneously. Zopounidis and Doumpos [51], for example, 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 [52] 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 after several validation tests.[8]

5.2.1 Selected examples of intelligence technique models and applications

Martin [24] is an early study that uses statistical methods, including both logit and DA, 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.

West [53] 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 com-

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

bined method of factor analysis and logit estimation is useful when evaluating banks' operating conditions.

Tam [54] uses the BPNN method for bankruptcy prediction. He utilizes data from Texas banks, one year and two years prior to their failures. He selects variables based on FDIC CAMELS criteria. He finds that BPNN has better predictive accuracy than other methods, in particular DA, factor, logistic and K-NN.

Tam and Kiang [55] compare the power of linear discriminant analysis (LDA), logistic regression, K-NN, Interactive Dichotomizer 3 (ID3), feedforward NN and BPNN on bank bankruptcy 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-year prior training sample. However, for holdout samples, BPNN outperforms the others in both the one-year prior and the two-year prior samples. In the jackknife method, BPNN also outperforms others in both the one-year prior and the two-year prior holdout samples. So, they conclude that NN outperforms the DA method.

Haslem et al. [23] determine the implication of the foreign and domestic strategies reflected in the balance sheets of U.S. commercial banks and the impact of these strategies on profitability performance. Their study analyzes 1987 data for 176 relatively large U.S. banks that have both foreign and domestic offices. Canonical analysis and the interpretive framework of asset/liability management are used to identify and interpret their foreign and domestic balance sheet strategies in the context of the crisis in lending to LDCs. They find a consistent dichotomy in foreign and domestic asset/liability matching strategies; the former is more conservative with respect to interest-rate and liquidity risks.

Bell [56] compares logistic regression and BPNN in predicting bank failures. In his study, he uses 28 candidate 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.

Olmeda and Fernandez [57] compare the accuracy, for bankruptcy prediction, of classifiers in a stand-alone model with a hybrid system, which integrates several classifiers. They propose a framework to formulate the choice of the optimal mixture of the technologies as an optimization problem and solve it using a genetic algorithm. Using the data from the Spanish banking system, they find BPNN performs the best, logit is the second best, and multivariate adaptive splines(MARS), C4.5 and DA follow in that order. The authors then combine models by a voting scheme and by a compensation aggregation method. They find that the prediction rates produced by the combined models are higher than the stand-alone model. Overall, Olmeda and Fernandez suggest that the BPNN model is superior to classical and new machine learning classifiers. They also find that hybrid methods by simple voting gave more accurate predictions than the stand-alone methods.

Alam et al. [58] present experimental results of Fuzzy Clustering and two self-organizing neural networks as classification tools for identifying potentially failing banks. They first describe the distinctive characteristics of the fuzzy clustering algorithm, which provides the probability that a bank will fail. Then they compare the results of the closest hard partitioning of fuzzy clustering with those of two self-organizing neural networks. They find that both the fuzzy clustering and self-organizing neural networks provide classification tools for identifying potentially failing banks.

Swicegood and Clark [59] compare DA, BPNN and human judgment in predicting bank failures. They use data from bank Call Reports. They find that the MDA model correctly classifies failures of 86.4% and 79.5% of regional and community banks, respectively. However, the BPNN model correctly classifies failures of 81.4% and 78.25% of regional and community banks. Thus, they conclude that BPNN outperforms other models in identifying underperforming banks.

Kolari et al. [26] develop an Early Warning system (EWS) based on logit regression 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, they use half of the original sample. 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.

Kao and Liu [60] formulate a DEA model for 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 presents the prediction of efficiency scores (also in ranges). They find that the predicted (with heir model) efficiency scores are similar to the actual (calculated from the data) efficiency scores. They also show that the bad performances of the two banks taken over by the Financial Restructuring Fund of Taiwan could actually be predicted in advance using their method.

Tung et al. [50] propose a new Neural Fuzzy system, the generic self-organizing Fuzzy Neural Network, based on the compositional rule of inference, GenSoFNN-CRI(S), to predict bank failure. The interaction between the features is captured in the form of IF-THEN rules. They compare the GenSoFNN-CRI(S) with Cox's proportional hazards model, BPNN and a modified cerebellar model articulation controller (MCMAC). They find that GenSoFNN-CRI(S) outperforms Cox's model in minimizing type-I error. However, GenSoFNN-CRI(S) yields higher type-II error. They also find that MLP outperforms both MCMAC and GenSoFNN-CRI(S).

Cielen et al. [61] compare the performance of Minimized Sum of Deviations (MSD), a DEA model and a rule induction (C5.0) model on the bankruptcy prediction problem. 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.

Canbas et al. [62] propose an integrated early warning system (IEWS) that combines DA, logistic regression, 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. With these three factors they employed DA, logistic regression and probit models. Then, 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; they conclude that the IEWS has more predictive ability than the other models under consideration.

Lanine and Vander Vennet [40] 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.

Boyacioglu et al. [39] apply various NN techniques, SVMs and Multivariate Statistical Methods to the bank failure prediction problem in Turkey; they compare the classification performances of the techniques tested. 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 multivariate statistical methods tested are multivariate discriminant analysis, K-means cluster analysis, and logistic regression analysis . The results show that MLP and LVQ can be considered the most successful models in predicting the financial failure of banks in the sample.

Kosmidou and Zopounidis [63] develop bank failure prediction models based on a multicriteria decision technique called UTilites Additives DIScriminants (UTADIS). A sample data of U.S. banks for the years 1993–2003 is used to develop a model that discriminates between failed and non-failed banks. The results show that the UTADIS multicriteria approach outperforms the traditional multivariate data analysis techniques such as discriminant analysis, supporting the fact that multicriteria techniques could be used efficiently for the bank failure prediction problem.

Ng et al. [64], proposes a novel fuzzy Cerebellar Model Articulation Controller (CMAC) model based on a compositional rule of inference called FCMAC-CRI(S), as a new approach to tackle the problem using localized learning. The new network is able to identify inherent traits and patterns of financial distress based on financial covariates derived from publicly available financial information. In FCMAC-CRI(S), its interactive relationships among the selected pattern features are captured in the form of fuzzy IF-THEN rules, which form the knowledge base of the EWS and provide insights into the factors of financial distress. Based on a population of 3,635 U.S.

banks observed over 21 years, the authors compare the performance accuracy of FCMAC-CRI(S) against Cox's proportional hazard model and the GenSoFNN-CRI(S) network model; based on the comparison, the performance of the new approach is better than the benchmark models.

Ravi and Pramodh [65] propose a new Principal Component Neural Network (PCNN) architecture for the bankruptcy prediction problem 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 principal components that perform the function of hidden nodes. Moreover, this study proposes an algorithm based on the Threshold Accepting (TA) meta-heuristic to train the PCNN. The efficacy of the algorithm is tested on Spanish and Turkish bank datasets. The results show the high generalization power of PCNN in 10-fold cross-validation. They also compare PCNN with the PCA-TANN and PCA-BPNN models. Based on the experiments conducted, they find that the proposed PCNN hybrids outperform other classifiers. In addition, the proposed feature subset selection algorithm is very stable and powerful.

Zhao et al. [47] compare the performance of two sets of classifiers for bank failure prediction. One uses raw accounting variables and the other uses several constructed financial ratios. Four methods are used to learn the classifiers: logistic regression, DT, NN, and K-NN. They evaluate the classifiers on the basis of expected misclassification cost under a wide range of possible settings. The results show that feature construction, guided by domain knowledge, significantly improves classifier performance.

An important message of the above review is that statistical techniques are frequently accompanied by intelligence techniques for better model performance in predicting bank failures. In most of the cases described above, intelligence techniques predict failures better than statistical models. Among intelligence techniques, NN is the most widely used method. Hybrid intelligence systems, which combine several individual techniques, are becoming more popular.

6 Concluding remarks

This article summarizes empirical Economics and Operations Research articles that aim to explain and find remedies for financial crises and bank failures in the United States and other countries. Using a combination of descriptive and analytical frameworks, we portray how and why a crisis in the relatively small subprime mortgage market has spread beyond the U.S. borders. Also, we provide an extensive review of Intelligence Techniques used in the Operations Research literature to predict bank failures and suggest that these techniques be applied in analyses of broader financial failures and crises.

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