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**Article**

## Elements of credit rating: A hybrid review and future research agenda

Cogent Business & Management

**Provided in Cooperation with:**

Taylor & Francis Group

*Suggested Citation:* Ubarhande, Prashant; Chandani, Arti (2021) : Elements of credit rating: A hybrid review and future research agenda, Cogent Business & Management, ISSN 2331-1975, Taylor & Francis, Abingdon, Vol. 8, Iss. 1, pp. 1-19,  
<https://doi.org/10.1080/23311975.2021.1878977>

This Version is available at:

<https://hdl.handle.net/10419/270212>

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To cite this article: Prashant Ubarhande & Arti Chandani | (2021) Elements of Credit Rating: A Hybrid Review and Future Research Agenda, Cogent Business & Management, 8:1, 1878977, DOI: [10.1080/23311975.2021.1878977](https://doi.org/10.1080/23311975.2021.1878977)

To link to this article: <https://doi.org/10.1080/23311975.2021.1878977>



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Received: 16 August 2020  
Accepted: 14 January 2021

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Reviewing editor:  
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## BANKING & FINANCE | REVIEW ARTICLE

# Elements of Credit Rating: A Hybrid Review and Future Research Agenda

Prashant Ubarhande<sup>1\*</sup> and Arti Chandani<sup>1</sup>

**Abstract::** Creditworthiness is acknowledged worldwide as focal point of debt processing. Credit Rate, an output of credit-rating process, reflects such credit-worthiness. We reviewed literature on elements of credit rating, viz. Credit Rate, credit-rating agencies (CRAs) and credit-rating model. Credit Rating is an independent evaluation of creditworthiness. CRAs perform this evaluation to support financial institutions in processing debts. Literature added in credit-rating domain from January 2001 to November 2020 is analyzed to explore the opportunities for further research. Bibliometric analysis is used to comprehend the existing literature. Subsequently, through structured review theories, methodologies used by researchers and CRAs are explored. Further, a hybrid literature review is developed by integrating bibliometric and structured review of research papers from widely recognized databases. A sample of 153 papers is constructed and studied to identify gaps in credit-rating domain and to develop suitable remedy to fill such gaps. We found that most of the studies emerged as after-effects of financial crisis reported in 2008 and 2016. The review revealed that 48% studies focused on development of new credit-rating mechanism without evaluating existing structure in-depth. This paper contributes to existing literature by encouraging researchers and CRAs to develop a sector-specific credit-rating system by evaluating existing models and

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Prashant Ubarhande, MBA (Finance) is a research scholar in faculty of Management at Symbiosis Institute of Management Studies, Symbiosis International (Deemed University), Pune, India. His research domain includes Credit Rating, Risk Management, Banking Regulations and Financial Engineering. Analysis of the credit-rating models and enhancements in the credit determination system are primary objectives of his research.

Dr. Arti Chandani, MBA (Finance) has been teaching since last 22 years in various B-school in India as well as in Brunei Darussalam. Her area of research is Corporate Finance, Banking, Corporate Governance and IT. She has more than 50 papers to her credit in peer-reviewed journals. Dainik Bhaskar awarded her National Education Leadership awards and Best Teacher in Financial Management. She has been organizing Annual Research Conference (SIMSARC) for Symbiosis Institute of Management Studies, India since 2013. She has also received multiple “Best Paper” awards in conferences.

### PUBLIC INTEREST STATEMENT

Acquiring financial support for organizational development is common among enterprises. Financial system enables access to debt based on creditworthiness. This paper analyzes the literature in credit-rating domain. Credit rates and Creditworthiness being critical elements of debt processing, review in this domain becomes important. To review the literature on said domain, we have collected relevant research content from Scopus and Web of Science. The collected papers were reviewed for their origin, objectives, methodology and contribution. To conclude the review, we have suggested to build a robust credit-rating infrastructure using advanced technology and statistics. Further, we have explored the possibilities of research extension in the domain of credit rating by suggesting a hybrid approach to determine credit rates.

improving them by adopting advanced techniques like Multiple Regression, Neural Networking and Artificial Intelligence. We have provided a feasible research agenda to further explore credit-rating domain. In this study we have identified that the factors determining creditworthiness are different for different sectors.

**Subjects: Corporate Finance; Banking; Business, Management and Accounting**

**Keywords: Credit rating; hybrid review; creditworthiness; CRAs; credit-rating models**

## 1. Introduction

Credit Rating is widely recognized to be among the most critical methods for assessment of creditworthiness. World, after 2008, witnessed emergence of strict financial regulations (Adegbite, 2018) which do include assessment of creditworthiness. Literature in credit-rating domain highlights its three elements viz. credit-rating models, credit-rating agencies, credit rates and factors to be considered in assigning credit rates. It is observed that since year 2001, 50% of the research is inclined towards development of new credit-rating model. Purpose of this review article is to analyze the existing literature from January 2001 to November 2020. The following paragraphs elaborate the importance of Credit Rating and credit-rating Agencies (CRAs).

Management of credit in terms of its availability, associated risk, aligned returns and payment default of customer availing credit facility is one of the key activities of lending organization. Credit-related activities such as credit allocation, credit distribution, credit procurement, credit recovery, etc., are undertaken by Banks, Financial Institutions (FIs) and Non-Banking Financial Companies (NBFCs) to determine creditworthiness of their clients. Every lending organization wants to ensure a full-proof management of risks associated with credit rendered. From mid of the nineteenth century, evaluation by an independent third-party justifying creditworthiness of the client is becoming popular to address the concerns related to risks associated with credit defaults. That was the era where world gained an index for credit worthiness in the form of credit rates (Rudden, 2015). Post Great Depression, system of credit rating was rooted as a consequence of a rule made by US Controller of Currency to restrict bank's purchases only to rated securities. Credit rates represent the degree of creditworthiness, signals the probability of payment default for individuals and predicts the degree of risk for a corporate or their products (Merriam Webster, 2020). Financial institutions refer credit rates determined by credit-rating agencies as a tool to assess credit risk.

Credit-rating Agencies (CRAs) are independent third parties determining credit rates of the entity based on financial performance. Credit-rating agencies contribute significantly in the debt processing and guide lenders on the creditworthiness of the client. Lenders often use information provided by CRAs to decide upon the cost of debt in the form of either interest rate to be applied on debt or repayment terms. For instance, a borrower with lower credit score is burdened with higher interest rate whereas borrowers having good credit rating were encouraged to borrow more at lower interest rates. In this way, opinion of CRAs is important for both lenders and borrowers. To enhance the literature on CRAs' contribution to financial market (Florian, 2016) examined the influence of credit rating on investors during the global financial crises. During these crises, business of CRAs was extensively critiqued and, since then, regulators have tried to reduce their power on financial markets. However, Florian justified the positive contribution of CRAs in financial markets even during financial crises. Conversely (Wickens, 2016) argued that CRAs could warn the financial market about such crises in advance. Precision of credit ratings in predicting financial distress diminish during financial crisis (Brezigar-Masten et al., 2015). Also, during such crisis, performance of the rating agencies was observed as being poor for structured finance (Sangiorgi & Spatt, 2017). A detailed literature review on elements of credit rating is provided in following section.

## 2. Literature review

To study the worldwide research contributions in this domain, literature from databases, viz. Scopus and Web of Science, during a period from January 2001 to November 2020 is considered. This section contains the review of literature on following elements:

- (1) Need to review the literature on contributions of CRAs and credit rates
- (2) Common factors considered by credit-rating agencies
- (3) Development of credit-rating model, and
- (4) Applications or contributions by both CRAs and credit-rating model.

However, scope of this paper is not limited to above elements.

### 2.1. Need to review the literature

According to (Kraus et al., 2020), it is important to check the availability of literature review in the domain under study. It is evident from initial screening and further mining of the research papers that only 10 research papers contributed towards review and that most of them were focusing on a particular technique of credit-rating model. A bibliometric review was not undertaken in the domain considering both credit-rating models and CRAs. Being an independent evaluator of creditworthiness of borrowers and securities, CRAs grabbed a substantial share of attention and glamour in the domain of credit evaluation, borrowing or lending, financial management and financial engineering (White, 2013). However, evaluation of borrowers for their creditworthiness by independent agencies (CRAs) witnessed more emphasis during the recovery period from any financial crisis such as crisis reported in 2008 and 2016 or non-financial crises such as pandemic. After such crisis, vigilance across the world in every financial transaction rises. Financial sectors witnessed the emergence and interference of the third party evaluators during this period. During recovery from the downfall due to pandemic of COVID-19, financial institutions shoulder a great responsibility of economic development by providing financial assistance, support and inclusion. Creditworthiness of the client is the buzzword now and this will emerge as mediator in successful financial transactions to determine the level of credit risk. In this paper, we have studied the literature available in the domain of credit rating and identified the inclination of researchers.

Discussion above justifies the importance of creditworthiness. CRAs determine the credit rates of the client on demand. To assign a rate to its client, CRAs use their unique methodology which varies from agency to agency and does not necessarily consider all factors applicable to determine creditworthiness. Borrowers or securities having different structure, operations and customers which they cater to should not be rated using similar methodology. Since CRAs assign rates to different borrowers using similar system, there exists a scope to doubt the reliability of such credit scores (Iyengar, 2012). We are living in the world of digitalization where technology is proved to be most dynamic driver. Emergence of digitization enables CRAs to expedite the credit evaluation process and derive the creditworthiness of clients or instrument. In order to construct a uniform view on creditworthiness of a client or instrument, its methodology and technology behind credit rates need to be understood. These submissions justify the need to study the mechanism and contributions made by CRAs. Proximate way to collect the research made on CRAs and credit rating is to study the available literature and enhance the same on the basis of current economic situations. Research papers of this domain are inclined towards developing new credit methodologies and not addressing the loopholes in existing system. Credit-rating models proposed by various authors are independent and carries unique methodology to determine credit rates. We recommend a hybrid model based on existing models instead of developing an entirely new system. CRAs can focus on developing a composite credit-rating model considering maximum factors to determine credit rates/scores for their clients.

## 2.2. Common factors considered by CRAs

Financial globalization brought with it increased dependence on financial institutions. Furthermore, blanket funding made credit ratings a crucial part of the funding and lending process (Bozovic et al., 2011). Financial indicators acquired great importance in determination of credit worthiness. Shanli Yu et al. suggested to consider the discriminatory power of financial and non-financial indicators to determine credit rates. Along with financial factors, non-financial factors should also be considered as important determinant of creditworthiness (Yu et al., 2018). The following section briefs about various factors considered and proposed to be considered in literature available.

Sustainability is an influencing parameter of creditworthiness. According to (Cubas-Diaz & Sedano., 2018), higher credit rates ensure better Sustainable performance. However, they remarked that the correlation between credit rates and sustainability was derived by studying traditional sustainability measures and not the novel quantitative sustainability performance measures. This necessitates the consideration of applicable sustainability factors for the entity being rated. Going concern is of utmost importance to any organization. Studies pertaining to 97 bankrupt companies (Cha et al., 2016) revealed that the credit rate and sustainability opinion are related to each other. The study suggests that an entity having good credit rating can sustain long. It was evidenced in Korea that higher credit ratings were assigned to family-owned businesses than non-family owned businesses. The reason for this is that the family-owned businesses had good governance strategies leading to positive effect on value of the business than the non-family-owned businesses (Chae & Oh, 2016). (Wiener-Fererhofer, 2017) agreed to this and concluded in his study that family-owned businesses achieve higher profitability and liquidity. However, the size of a firm represents no significant differences between family-owned and non-family owned firms.

Internal competition between CRAs contributes little in determining credit rates (Bae et al., 2015). On comparing the market share, competition and ratings of “Fitch Ratings” which is an American CRA, it can be proposed that neither competition nor CRAs inflate firm’s rating without success stories (Bae et al., 2015). Similarly, recognition of CRA by certain authority has least impact on ratings process (Bruno et al., 2014). Information provided to the CRAs by clients plays important role in determining credit scores. If manipulated information is provided to CRAs, credit rates so determined will not reflect the real creditworthiness of client (Zhao, 2017). Therefore, transparency in the credit rating is important factor for CRAs to earn trust of clients, investors and regulators. To raise the confidence of these users, CRAs must focus on development of an effective mechanism for identifying potential factors responsible for arising conflicts of interest (Rebryk et al., 2017). (Chang et al., 2017) challenged the contribution of CRAs by developing a credit-rating model that can rate firm without involving CRAs. The said model used generic indices, area under curve (AUC) of receiver operating characteristics (ROC) and log loss.

Adoption of International Financial Reporting Standards (IFRS) is beneficial in upgrading credit ratings. Standard procedures ensure compliance of most of the performance parameters and lead to improve the credit rating (Daskalopoulos et al., 2016).

Credit rates of any entity should be determined on the basis of economic factors applicable to that sector or company as the strength and direction of different economic factors is different (Kaniowski et al., 2016). Turnover in real assets have a considerable impact on credit ratings (Venkiteswaran, 2014). CRAs do link cost of debt or interest rates with creditworthiness and credit rates assigned to client (Raghunathan & Varma, 1992).

Data preprocessing is key factor in determining the credit rates rather than focusing directly on employing various data mining techniques (Hsu-Che et al., 2014). Differences in the methodologies adopted to determine credit rates by CRAs result in differences in rating properties (Bonsall et al., 2016). Bonsall et al. have focused the constraints in information processing between Standard & Poor’s and Egan Jones Ratings Company and concluded that Egan-Jones’ rating accuracy decreases with rise in information uncertainty. This reveals a fact that the credit rates announced



by CRAs having least access to the financial and related information might be overestimated and does not reflect actual creditworthiness of the client. Therefore, the focus of credit-rating system should be holistic covering entire structure rather than considering limited or single indicator (Yu et al., 2018). Research papers suggested various techniques and input factors to determine credit score. In the next section we have elaborated researcher's contribution in the domain as credit-rating models.

### 2.3. Credit-rating models

Credit-rating models support credit approval decisions by assigning credit rates to debtor suggesting its creditworthiness. These models are critical part of financial system as they provide necessary infrastructure to determine the credit rates, a driver of creditworthiness. CRAs use varied methodologies to assign the credit rates to their client. Traditionally, methodologies including statistical analysis such as discriminant analysis, logistic regression and decision tree were common techniques to develop these models (Thomas, 2000). Use of statistical techniques in developing credit-rating models yield synergetic results in linear system. When a nonlinear relationship exists, the accuracy of these models decreases (Huang et al., 2004). One of the studies conducted in Taiwan on 45 credit-rating models suggest that the model based on Bagging-Decision Tree (Bagging-DT) technique was efficient upto 83% (Hsu-Che et al., 2014).

During late the 20th century (Black & Scholes, 1973) and (Merton, 1974) of Massachusetts Institute of Technology (MIT) proposed a structured framework based on the financial parameters to model the credit risk. Predicting a default to its 100% accuracy is not possible with any of the credit-rating models. After studying a credit risk prediction using z-score approach (Agarwal & Taffler, 2008) suggested that market-based models which consider financial information for credit risk prediction are robust and cannot be replaced. However, the performance can be improved using innovative approaches and by embedding applicable information. World has witnessed the technological revolution in recent past and hence in the financial sector. Use of advanced techniques such as neural networking and advanced regressions to develop credit-rating model is trend of current times. Since these techniques have better predictive ability, studies inclined more towards use of these techniques in developing credit-rating models.

Future rating of a firm depends both on its current and previous rates. Probability of downgrades in credit rates increases if a firm is rated lower than its previous ratings; this concept is called as rating momentum. (Pasricha et al., 2017) addressed rating momentum by developing a credit-rating model using Markov regenerative process (MRGP) and semi-Markov process (SMP). Further (Reis et al., 2020) concluded that rating momentum considered under non-Markov model has a larger impact on transition probabilities and hence it predicts creditworthiness effectively than default Markov models. Principal component analysis and cluster analysis can be effectively used to assign the credits to small firms (Yoshino & Taghizadeh-Hesary, 2015).

Information Uncertainty is major constraint in developing a robust credit-rating model. To overcome the issue of uncertainty, fuzzy reasoning has been applied while developing a credit-rating model (Dwivedi & Tripathi, 2019). Fuzzy Neural Networks, specifically nonlinear relationships in a system can erudite through Artificial Neural Networks (ANN) and can bring maximum accuracy in determining credit rates (R. H. Abiyev, 2014). Along with ANN, technique of Support Vector Machines (SVM) is widely used to determine the credit rates of entities. Monotonicity is the major constraint in SVM-based model. A monotonicity constrained model developed by (Chen & Li, 2014) addressed the loss of monotonicity in the data and improved the performance of rating mechanism over traditional SVM. Lending organizations can verify credit rates assigned to entities using support vector machine technique effectively than BP neural network assessment model (Zhang et al., 2015). Developing robust loan pricing system is one of the crucial activities in credit management. credit-rating model contributes reasonably in construction of such system (Y. Zhang & Chi, 2018).

Under decision tree periphery, Random Forest technique has more forecasting capacity, therefore applying such technique in variable selection and forecasting generates effective credit rates (Wu & Wu, 2016). Market-based information adds value in credit-rating predictions; this information can be evaluated using Moody's KMV. Verifying such predictions with the help of Random Forests (RF) and Rough Set Theory (RST) yields meaningful credit rates (Yeh et al., 2012). Multi-criteria decision-making (MCDM) technique based on a linear programming employing measurement of distance-to-default to predict credit rates evidenced more popularity over obtaining rates merely based on financial ratios (Douplos et al., 2015). Differentiating between types of default is very challenging task and even could not be achieved through existing credit-rating models (Ju & Sohn, 2017). To overcome this gap (Ju & Sohn, 2017) proposed the application of quantification scores to determine the credit scores. In this technique, researchers identified that technology and profitability factors such as technology development, technology superiority and sales would determine whether an organization would default or not.

Techniques such as Probit and stepwise regression are popular and for many years have been successfully applied to determine credit rates. However, a model based on rank sum test and rank correlation analysis predicts the credit rating of a new loan customer with increased accuracy (Guotai & Zhipeng, 2017). Ordered Probit analysis can be effectively applied to construct a credit-rating model competent of addressing two important issues, changing economic environment and long-term validity of rates (Balios et al., 2016).

According to Basil and Elgammal, credit rates and the default probabilities behave inversely; i.e. with higher ratings, the tendency of bankruptcy and default minimizes (Basil & Elgammal, 2013). Additionally, an innovative fluctuating credit ratings model can be developed using Merton structural credit model. In this technique, fluctuations in the asset are combined with capital structure, Distance to Default (DD) and Probability of Default (PD) to measure creditworthiness (Edmund et al., 2013).

This section suggested the methodologies adopted by various researchers and CRAs in developing credit-rating models. It is understood from the above paragraphs that both CRAs and researchers in the domain evolved with time. Appropriate technique, applicable factors and credit score generated has acquired different definition according to financial environment and infrastructure. To assign credit rates, traditionally basic techniques such as weighted averages or Markov chains were used, but now advanced techniques such as AI and ML are popular. In future, the models based on traditional techniques will be replaced by models developed using advanced techniques as the concept of credit rating and creditworthiness is dynamic in nature. For instance, during the financial downfall in COVID-19 pandemic, lenders have restricted the extension of credit facilities. This suggests that a credit-rating model should be flexible enough to generate the credit scores or rates as per current financial environment. The following section highlights the scope and contributions of credit rates.

#### **2.4. Credit rates/scores—applications and contributions**

Credit rate or credit score assigned by CRAs using credit-rating models represents the creditworthiness of company rated. To process debt, financial institutions such as banks are dependent on predictions related to credit rating. This dependency made determination of credit rates a critical concern. Also, credit-rating prediction influences decisions related to raising funds. (Bae & Kim, 2015). Credit rate of the company determines its corporate lifecycle. Companies with higher credit rating have tendency to sustain for longer duration coupled with a low probability of becoming a defaulter (Machek & Hnilica, 2013). Financial information, whether positive, reflecting strengths of the company or negative, reflecting weaknesses of the company, accordingly affects credit rates and attracts the revisions in assigned rates (Cho & Choi, 2015). Improved credit rates enable company to attract investors and help to acquire capital at lower cost. (El-Masry, 2016) argued that credit rating is an important determinant of capital structure. (Rogers et al., 2016) have contradictory views on utility of credit rate. In 2016, Rogers et al. observed that credit-rating



revision does not provide any foundation to capital structure decisions. Changes in the credit rates impact the issuance of debts by lenders, but if such change is marginally small and does not pull the firm in lower rating range or push it to higher rating range, then said impact is negligible (Bora et al., 2019). Rating inflation depends on rating quality constraints as well as the relative demand by constrained and unconstrained investors (Josephsona & Shapiro, 2020). Such diverse conclusions on utility of credit rates in financial decisions necessitates further research in this domain and justifies the requirement of uniform methodology to determine the credit rates.

Acquiring credit rates from international agency does not add considerable value to creditworthiness of company. There are no significant evidences to prove the advantage of acquiring credit rates from international CRAs over domestic agencies. Rather, credit rates are the quantitative output of financial data. (Han & Reinhart, 2018) argued that presence of asymmetric information results into lowering the credit rates and dissatisfaction to the lenders or investors. Relevance of credit rates assigned by CRAs depend on the costs. It was evidenced that information related to cost is more relevant in recessions than in expansions when agency costs are low (Fieberg et al., 2016). Companies hiring credit-rating analyst to cater the credit rating-related matters have reported increase in the value of their securities; however, such hiring does not impact equity of the employer company (Aktug et al., 2015). On the other hand, contribution of credit rating to structured financial product is limited. Dependency on external ratings to determine the creditworthiness should be defined and its scope in the credit appraisal should be defined with proper weights assigned by lending institutions (Tanja et al., 2019).

Positive credit history and acceptable credit rates aid debtors to avail debts at lower interest rates, greater flexibility and with longer payment terms (Liu et al., 2019). Accurate prediction about creditworthiness is possible if credit rate is based on all relevant data including private information about customers and companies without compromising the secrecy and confidentiality of such information (Brocardo et al., 2017). To address concern of secrecy and confidentiality, they have proposed application of cryptographic protocol. Firms with higher credit rates have positive impact on dividends and poor-rated firms are more inclined towards negative dividend predictors. This suggests that credit rating contributes towards predicting dividend strategy of a company (Taekyu & Injoong, 2020).

Sections above highlighted various views and research conclusions in credit-rating domain. Authors have diverse views when addressing concerns related to CRAs, credit-rating models and applications of credit rates. The following section depicts methodology adopted to perform literature analysis and review.

### **3. Methodology**

Basic objective of this paper is to perform a literature review to identify the contribution made in domain of credit rating for two decades (January 2001 to November 2020) and to suggest the scope for future research. Since 1934, 1886 research papers were added in Scopus (1114) and Web of Science (772) on “credit rating.” Out of these 1886, only 62 (3.28%) research papers were added before year 2001. Between January 2001 and November 2020, 96.72% research papers were added to databases; hence, we considered this period for analysis. Our paper is an amalgamation of both structured and bibliometric review (hybrid review as per (Paul & Criado, 2020)). To ensure robust literature review, we have defined the review protocol in following paragraphs. Review protocol enumerates the search criteria, the databases, construction of sample, the criteria for including or excluding literature, quality criteria and so on (Pittaway et al., 2014).

#### **3.1. Literature search criteria**

We have selected papers from widely recognized databases such as Scopus and Web of Science (WoS). Papers published by Elsevier, Sage Publication, Taylor and Francis Group, Emerald Insight, Inderscience, etc. form the sample of 153 research papers. Following section enumerates the process of selecting papers for review.

### 3.2. Sample construction

Databases including Scopus and Web of Science are chosen to study the available literature in domain of credit rating. We have extracted research articles from said databases and filtered them by applicable keywords such as credit rating, credit-ratingmodel, etc. Scopus and Web of Science are most appreciated databases in the world. They provide scientific sources and research materials in all disciplines. Editorial committees of journals listed in these databases and the publishers affiliated with them (Taylor and Francis Group, Elsevier, Sage Publication, Emerald Insight, Inderscience, etc.) ensure the selection of the best research works for publication. Following figure suggests the data extraction and synthesis.

- a. In first mining, 654 from Scopus and 124 relevant papers from Web of Science were extracted
- b. Out of these 778, we identified 217 (167 and 50 from both database as sequenced) papers on the basis of keywords such as credit-rating model andCRAs
- c. These 217 papers were further reviewed and 153 relevant papers were identified as sample. During this review, papers containing research onCRAs, factors identified in credit rate determination and literature review on credit rating were selected.

### 3.3. Quality criteria

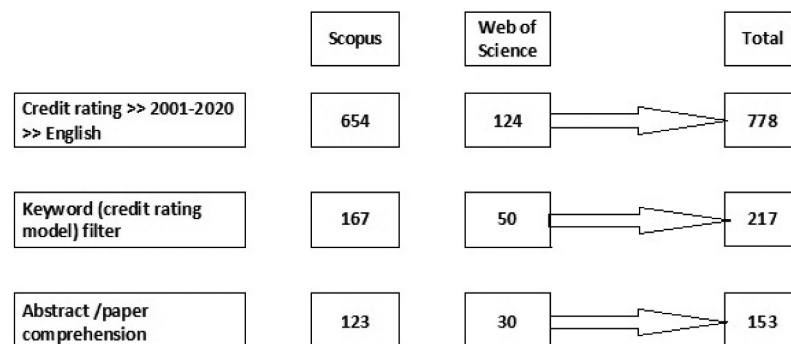
We have followed “concept centric approach” to filter and review 217 papers obtained on the basis of key words. Concepts including inclusion of credit-ratingmodel or agencies, techniques, review on credit-rating domain, factors used in determining credit rates and model comparison were considered. We have not used an author centric approach in this paper as it may not be suitable for a successful literature review. The primary reason for not using author centric approach is that an author centric approach generates summary and not synthesis (Webster & Watson, 2002) [Figure 1](#).

### 4. Analysis and discussions

Literature in credit-ratingdomain is rich in its wide availability and variability. We have performed bibliographic analysis and explored the collected literature under following analysis heads:

- (1) Year-wise and Decade-wise Distribution
- (2) Geographical Distribution
- (3) Source Database Distribution
- (4) Common Industry Undertaken
- (5) Objectives and Key Contributions of Research
- (6) Theories and Methods Used in Research

**Figure 1. Data extraction and synthesis.**



#### 4.1. Year-wise and decade-wise distribution of research publications

Selected research papers published in two databases Scopus and WoS has yearly and decade-wise distribution as shown in Figure 2 and Figure 3

85% of the contributions in terms of research papers under study are published during January 2011 to November 2020. There is sharp rise in the research contribution in second decade over first. Referring to the yearly distribution, we have concluded that the contribution was constant from 2009 to 2011. However, after 2011 the domain witnessed a sharp ascend in number of papers and this ascend continues thereafter. This suggests that credit-rating awareness, modifications, regulations and techniques did emerge with increasing rate after 2011. CRAs lacked reliability on different fronts that has led relevant authorities to regulate these agencies for their objectivity (Lopatta et al., 2019). Windfall increase in the contribution on credit-rating literature during 2008 clearly indicates the requirement of updates or increase in scope post financial crisis. During 2007–08, world experienced financial crises due to catalytic rise in number of cases related to residential mortgage defaults (Murphy, 2008). Post said crises, the financial sector has witnessed emergence of legal policies and regulations vis-à-vis determination of credit worthiness gained substantial importance. Increase in the research contribution supports the same. Similarly, a sharp increase in the literature is observed during 2019. There is 93% increase in research contribution post 2018 financial crisis. Figures above and subsequent discussions advocate an

Figure 2. Decade-wise distribution of research papers.

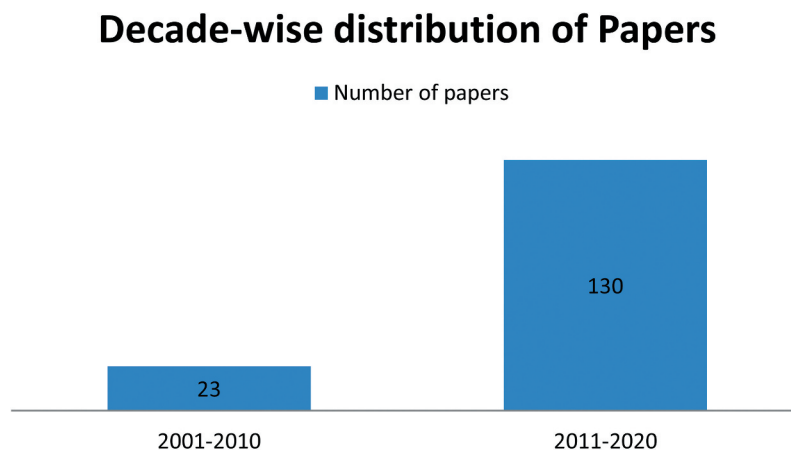
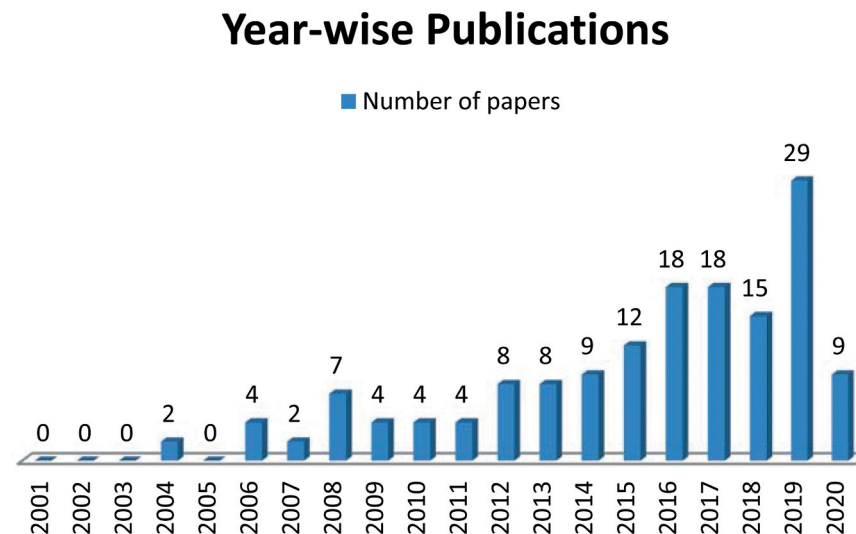


Figure 3. Year-wise distribution of research papers.



existence of a pattern in contribution by authors towards credit-rating domain. More literature is added soon after financial crisis.

#### 4.2 Geographical Distribution of Related Research over Two Decades from January 2001 to November 2020

Sample of 153 papers is distributed demographically as per Figure 4. For this analysis, research papers collected were divided based on country where the research was conducted and further labeled under America (North and South), Asia, Europe, Africa and Australia.

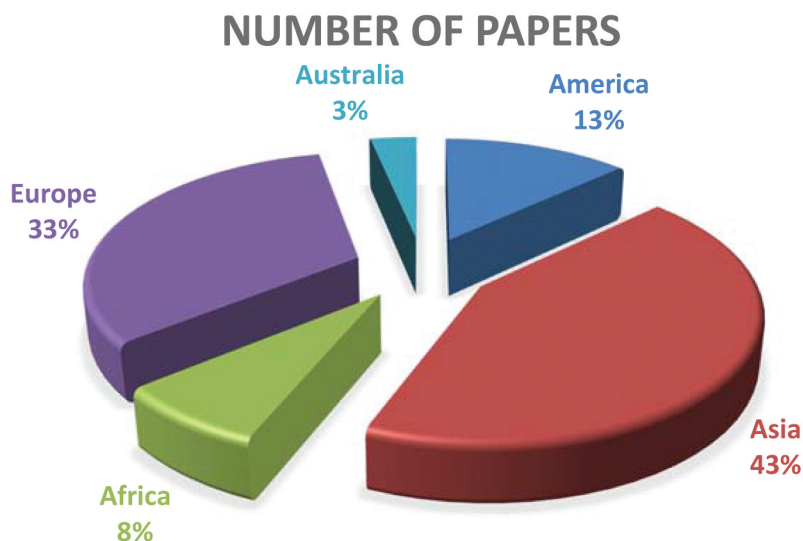
Asia and Europe (Eurasia) witnessed 76% of the total research under consideration. In the countries of Europe and Asia, financial concerns and regulations are accompanied by unstable political environment (Vyacheslav, 2019). This leads to have varied views on regulations, hence Eurasia has recorded highest number of papers during the period (January 2001 to November 2020) under study. Adoption of banking regulations such as Basel norms and financial crisis are main reasons for rigorous credit-rating evaluation and research in the said domain. Lending institutions are concerned about credit ratings to price the debt (Tanja et al., 2019), (Raghunathan & Varma, 1992).

#### 4.2. Industry undertaken for research

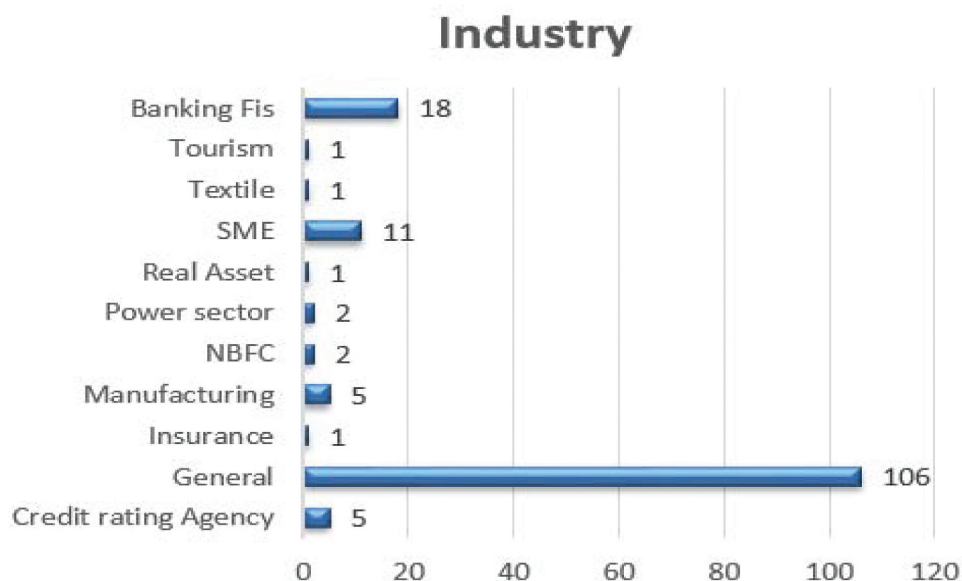
Credit-rating mechanism, factors considered, rationing of factors and impact of credit rates varies according to nature of company or instrument being studied. Industry-specific analysis is quite relevant and important as credit rates are highly influenced by nature of inter-industry and intra-industry transfer of information (Abad et al., 2020). Figure 5 indicates the types of industries undertaken for research during two decades (January 2001—November 2020)

Researchers while studying credit rating, preferred the general sector for data collection and analysis. This is because most of the studies revolved around either CRA database or financial statements. If a sample is refined for specific industry, then data collection and analysis is a challenge. Scope of outcomes and its applicability can be increased by considering all industries for data collection and analysis. The second most preferred sector for analysis is banking and financial institutions because this sector is the primary user of credit-related information.

Figure 4. Demographic distribution of research papers.



**Figure 5. Industry considered for research on credit rating.**

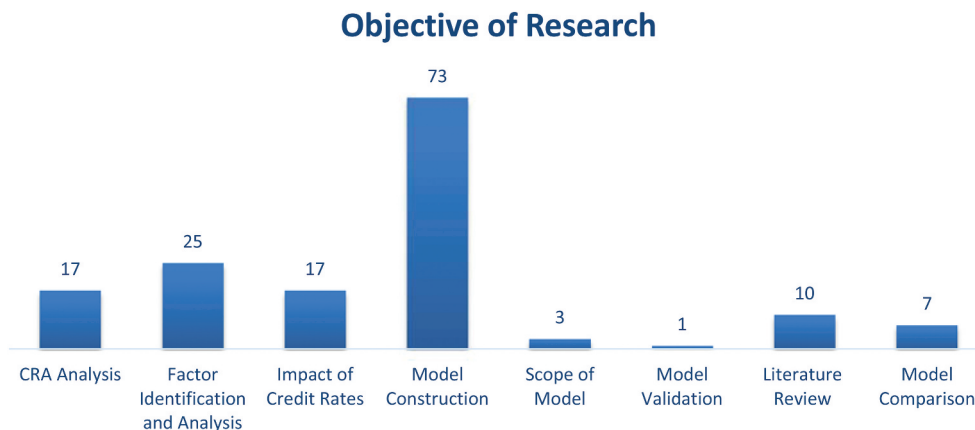


#### 4.3. Objectives and key contributions of research

It is important to analyze objectives, type of data and methodologies used by researchers to construct a healthy literature review (Light & Smith, 1971). CRAs consider mainly financial data of the organization or instrument to assign the credit rates. During last two decades, researchers have considered both primary and secondary data to explore credit-rating determination, credit-rating model development and validating the scores assigned by CRAs. Out of the 153 research papers selected as sample, 150 studies found to be based on secondary data. These 150 research papers include literature review papers, model comparisons, model validations, comparisons of CRAs, etc.

Figure 6 represents the primary objective of research undertaken. During January 2001 to November 2020, 73 (48%) studies contributed to the present body of literature by constructing a new credit-rating model. Table 1 represents the cluster classifications of theories and methods used by these 73 researchers to construct credit-rating models.

**Figure 6. Objective of research.**



**Table 1. Theories and methods used to construct credit-rating model**

Key Authors	Methodology Used	Cluster Defined	Number of papers recorded
(Pasricha et al., 2017), (Dos Reis et al., 2020)	Markov Chains	Markov Chains	4
(Kaniowski et al., 2016)	Monte-Carlo simulations		
(Y. Zhang & Chi, 2018)	Multi-objective Programming	Artificial Intelligence and Machine Learning	22
(Michael & Constantin, 2011)	Multi-criteria Outranking Modeling		
(Hsu Che et al., 2014)	Bagging-DT		
(K.-j. Kim & Ahn, 2012), (Mileris & Boguslauskas, 2011)	Artificial Intelligence		
(Dwivedi & Tripathi, 2019), (Shi et al., 2016) (R. H. Abiyev, 2014) (Cao & Xiong, 2014), (Guo et al., 2012), (Gong, 2017), (Baofeng et al., 2016), (Wu et al., 2016), (Estevez & Carballob, 2015), (Al-Najjar & Al-Najjar, 2014), (Guo et al., 2012), (Hongxia et al., 2010), (Shyu, 2008), (Jiang, 2007), (Kao & Wang, 2006), (D. Zhang & Zhang, 2004)	Neural Network		
(Wu & Wu, 2016)	Random Forest (RF)		
(Taba et al., 2019)	Novel Algorithm	Data Mining	5
(Bae & Kim, 2015), (Hristova et al., 2017), (Moradi & rafiei, 2019), (G. Li et al., 2018)	Data Mining		
(Balios et al., 2016), (Fan et al., 2008)	Probit Analysis	Regression Analysis	23
(Bloechlinger & Leippold, 2018), (Habachi & Benbachir, 2019)	Discriminant Analysis		
(Polito & Wickens, 2014)	Default probabilities		
(Doumpos et al., 2015), (Allen & Singh., 2016),	Distance to Default		
(Yu et al., 2018)	K-S test		
(Ju & Sohn, 2017) (Angilella & Mazzu, 2015) (Huang et al., 2004) (Mileris & Boguslauskas, 2011), (Guotai & Zhipeng, 2017), (Fouriei et al., 2016), (Evgenidis et al., 2016), (Fouriei et al., 2016), (Ven et al., 2018), (Ding et al., 2019), (Qiu, 2019), (Chi & Meng, 2019), (Wei et al., 2010), (Y. Kim & Sohn, 2008)	Regression Analysis		

(Continued)



Key Authors	Methodology Used	Cluster Defined	Number of papers recorded
(Yeh et al., 2012)	Rough Set Theory (RST)	Other Quantitative Methods	19
(Zhang et al., 2015), (K.-j. Kim & Ahn, 2012), (Chen & Li, 2014), (Chen et al., 2011), (Lee et al., 2010), (Hsu & Hung, 2009)	Support Vector Machine (SVM)		
(Z. Li et al., 2013), (Bae, 2019)	Weighted Averages		
(Shi et al., 2019), (Shi et al., 2016)	Loss Given Default		
(Tounsi et al., 2018), (Chang et al., 2017)	Area Under the Curve		
(Xu & Zhang, 2017)	Analytic Hierarchy Process		
(Doumpos & Figueira, 2019), (Angilella & Mazzu, 2015)	ELECTRE TRI		
(B. Li et al., 2019)	Principal component analysis		
(Gavalas & Syriopoulos, 2014)	Optimisation		
(Satchidananda et al., 2007)	Technology Based		

Research contributed in the abovementioned period from January 2001 to November 2020 is covering major eight aspects of domain viz. CRA analysis, Factor identification and analysis, Impact of credit rates, Model construction, Scope of model, Model validation, Literature review and Model comparison. The first preference researchers gave was to develop the model; however, identification of factors affecting credit policy was also the area of interest for 25 (16%) studies. Analysis of CRAs and impact of credit rates was studied in 11% papers. This statistics suggest that there exists a scope to study the existing models than creating new ones to recognize the gap in existing methodology and thereby improve the same. Scope of the model, its validation and model comparison are contributing only 07% as these studies required collection of appropriate financial data and further analysis. According to (Habachi & Benbachir, 2019), collection of appropriate data is primary requirement to ensure reliable results. Scope of the model, its validation and comparison witnessed least attraction on account of limitations of data availability. Development of new credit-rating models common to all sectors may not be helpful to determine appropriate creditworthiness as factors determining creditworthiness varies sector wise. Therefore, we proposed that a sector-specific model shall be developed and the same can be upgraded from time-to-time.

The scope of 10 (07%) literature review papers is to study the impact of credit ratings on pricing the financial products and to study CRAs. 50% (05) literature review papers advocate the requirement of improvements in existing credit-rating models (Wang et al., 2015).

Neural Networking (a technique under Machine Learning) and Regression are popular methods at all times to construct a credit-rating model to determine credit rates. During recent past, techniques under Machine Learning such as Neural Networking, Fuzzy Logic and Random Forest (RF) are getting popularity and wide scope in finance and portfolio management sector (Huck, 2019). Post 2008 financial crisis, use of technology based methods and approaches to construct

credit-rating model emerged. Due to scientific approach and evidence-backed methodologies, regression and neural networking evidenced the highest share. Complexity of modern problems is increasing and, hence, techniques such as Regression, Artificial Intelligence and Machine Learning are becoming popular among researchers (Apsemidis et al., 2020). Table 1 demonstrated that from January 2001 to November 2020, 62% studies involve use of techniques such as Artificial Intelligence, Machine Learning and Regression. Techniques such as neural networking under machine learning yield accurate results, even for the data containing errors. Researchers found these techniques as a useful tool to perform quantitative analysis and developments over traditional quantitative techniques such as Markov Chains, Area under the Curve, Weighted Averages, etc.

## 5. Conclusion and scope for further research

This paper contains a review of literature available in the domain of credit rating from January 2001 to November 2020. On the basis of detailed analysis of research papers on credit rating for their objectives, methodologies used, sources and types of data collected, location of research, etc., over two decades, we have concluded that majority of the studies are inclined towards development of new framework and add such new framework to the existing body of knowledge. With technological advancements, Regression, Artificial Intelligence and Machine Learning (Neural Networking) are gaining popularity and wide acceptance. It is identified that during the last 20 years, only 30.72% (47 out of 153 total papers) industry-specific studies were conducted including Banking/Finance and small and medium-size enterprises (SMEs) sectors. This finding shall help researchers to develop industry-specific research agenda on credit rating. Industries such as manufacturing, food and beverages, agriculture and allied businesses were not included in this to study the credit rating. As sectors such as manufacturing, food and beverages, agriculture and allied businesses require external funding, their creditworthiness becomes crucial. Researchers can focus on these sectors to identify factors determining their creditworthiness and can explore the exclusive technique to determine credit rates.

Solutions to financial crisis consume critical capital and require huge investments. According to (Murphy, 2008) and (Adegbite, 2018), financial regulations and controlling mechanism developed within the organization may help in healing from default crisis. We found that most of the studies were conducted immediately after the financial crisis and were concentrated on development of new credit-rating mechanism, whereas improvements and critics to existing mechanism received limited attention. Addressing limitations of the existing system and suggesting remedy for the same would be both cost-effective as it will not attract cost of developing entire new model and resistance free as the same is built on existing system. Therefore, this review will provide a motivation to researchers to focus more on existing credit-rating methodologies and identification of gaps therein rather than developing a new methodology. One of the prime conclusions of our review includes identification of need to develop a hybrid credit-rating mechanism by integrating different methods such as machine learning techniques, regression analysis, super vector machines, etc. Researchers and lenders in this domain shall explore the development of credit rating by considering the views proposed in this review. Credit-rating models based on these advanced tools and techniques will only sustain in future. Present paper and the conclusions drawn are in association with research material collected and filtered as mentioned in relevant sections. Researchers shall take this further by considering more keywords and enlarging the period under study. For future research, industry-specific analysis in all the elements of credit rating and hybrid model by merging advanced quantitative techniques with qualitative information to determine credit rate are key takeaways of this paper.

### Acknowledgements

We, Prashant Ubarhande and Dr. Arti Chandani, would like to thank the editor/s and reviewers of this research article for their kind considerations and suggestions.

### Funding

The authors received no direct funding for this research.

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### Citation information

Cite this article as: Elements of Credit Rating: A Hybrid Review and Future Research Agenda, Prashant Ubarhande & Arti Chandani, *Cogent Business & Management* (2021), 8: 1878977.

### References

- Abad, P., Ferreras, R., & Robles, M. (2020). Intra-industry transfer effects of credit risk news: Rated versus unrated rivals. *British Accounting Review*, 52(1), UNSP 100815. <https://doi.org/10.1016/j.bar.2018.12.002>
- Abiyev, R. (2014). Credit rating using type-2 fuzzy neural networks. *Mathematical Problems in Engineering*, 2, 1–8.
- Abiyev, R. H. (2014, March 27). Credit rating using type-2 fuzzy neural networks. *Mathematical Problems in Engineering*, 2014, 1–8.
- Adegbite, G. (2018). 2008 Global financial crisis-ten years after; is another crisis 'resonating'? *SSRN Electronic Journal*, 1–11.
- Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance*, 32(8), 1541–1551. <https://doi.org/10.1016/j.jbankfin.2007.07.014>
- Aktug, R. E., Nayar, N. (. & Salas, J. M. (2015, August). Are credit rating agency analysts valuable? *Journal of Risk Finance*, 16(4), 378–394. <https://doi.org/10.1108/JRF-11-2014-0159>
- Allen, P., & Singh. (2016). A dynamic credit ratings model. *Journal of Risk Model Validation*, 10(1), 59–80.
- Al-Najjar, D., & Al-Najjar, B. (2014). Developing a multi stage predicting system for corporate credit rating in emerging markets Jordanian case. *Journal of Enterprise Information Management*, 27(4), 475–487. July 8. <https://doi.org/10.1108/JEIM-09-2012-0071>
- Angilella, S., & Mazzu, S. (2015). The financing of innovative SMEs: A multicriteria credit rating model. *European Journal of Operational Research*, 244(2), 540–554. <https://doi.org/10.1016/j.ejor.2015.01.033>
- Apsemidis, A., Psarakis, S., & Moguerza, J. (2020). A review of machine learning kernel methods in statistical process monitoring. *Computers & Industrial Engineering*, 142, AN106376. <https://doi.org/10.1016/j.cie.2020.106376>
- Bae, D. S. (2019). Internal credit rating framework for real asset investment. *International Journal of Strategic Property Management*, 01–13.
- Bae, J. K., & Kim, J. (2015, February 9). A personal credit rating prediction model using data mining in smart ubiquitous environments. (D. Sauveron, Ed.). *International Journal of Distributed Sensor Networks*, 2015(1), 6. <http://dx.doi.org/10.1155/2015/179060>
- Bae, K.-H., Kang, J.-K., & Wang, J. (2015). Does increased competition affect credit ratings? A Reexamination of the effect of fitch's market share on credit ratings in the corporate bond market. (J. Harford, Ed.). *Journal of Financial and Quantitative Analysis*, 50(5), 1011–1035. October 5. <https://doi.org/10.1017/S0022109015000472>
- Balios, D., Thomadakis, S., & Tspouri, L. (2016). Credit rating model development: An ordered analysis based on accounting data. *Research in International Business and Finance*, 38, 122–136. September 1. <https://doi.org/10.1016/j.ribaf.2016.03.011>
- Baofeng, S., Nan, C., & Jing, W. (2016). A Credit rating model of microfinance based on fuzzy cluster analysis and fuzzy pattern recognition: Empirical evidence from Chinese 2157 small private businesses. *Journal of Intelligent and Fuzzy Systems*, 31(6), 3095–3102. December. <https://doi.org/10.3233/JIFS-169195>
- Basil, A.-N., & Elgammal, M. M. (2013). Innovation and Credit Ratings, does it matter? UK evidence. *Applied Economics Letters*, 20(5), 428–431. <https://doi.org/10.1080/13504851.2012.709589>
- Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81 (3), 637–659. <https://doi.org/10.1086/260062>
- Bloechlinger, A., & Leippold, M. (2018). Are ratings the worst form of credit assessment except for all the Others? *Swiss Finance Institute Research Paper*, 1–62.
- Bonsall, S., Koharki, K., & Neamtiu, M. (2016). When do differences in credit rating methodologies matter? Evidence from high information uncertainty borrowers. *Accounting Review*, 92(4), 53–79. October. <https://doi.org/10.2308/accr-51641>
- Bora, A., Celik, S., Abdulla, Y., & Alshakhoori, N. (2019). The impact of credit ratings on capital structure. *Isra International Journal of Islamic Finance*, 11(2), 226–245. December 9. <https://doi.org/10.1108/IJIF-03-2018-0028>
- Bozovic, M., Urosevic, B., & Zivkovic, B. (2011). Credit rating agencies and moral hazard. *PANOECONOMICUS*, 2 (2), 219–227. June. <https://doi.org/10.2298/PAN1102219B>
- Brezigar-Masten, A., Masten, I., & Volk, M. (2015). Discretionary Credit Rating and Bank Stability in a Financial Crisis. *Eastern European Economics*, 53(5), 377–402. September. <https://doi.org/10.1080/00128775.2015.1086885>
- Brocardo, M. L., Rolt, C. R., Dias, J. D., Custodio, R. F., & Traore, I. (2017). Privacy information in a positive credit system. *International Journal of Grid and Utility Computing*, 8(1), 61–69. <https://doi.org/10.1504/IJGUC.2017.082136>
- Bruno, V., Cornaggia, J., & Cornaggia, K. (2014, October 12). Does Regulatory Certification Affect the Information Content of Credit Ratings? *Management Science*, 1–47. SSRN, Elsevier Inc. <https://ssrn.com/abstract=1962840>
- Cao, Y., & Xiong, S. (2014). A sustainable financing credit rating model for china's small- and medium-sized enterprises. *Mathematical Problems in Engineering*, 1–5.
- Cha, M., Hwang, K., & Yeo, Y. (2016). Relationship between audit opinion and credit rating: Evidence from Korea. *The Journal of Applied Business Research*, 32(2), 621–634. March. <https://doi.org/10.19030/jabr.v32i2.9599>
- Chae, S.-J., & Oh, K. (2016). The effect of family firm on the credit rating: Evidence from Republic of Korea. *The Journal of Applied Business Research*, 32(6), 1575–1584. December. <https://doi.org/10.19030/jabr.v32i6.9809>
- Chang, C., Liou, H., Shih, W., & Ho., (2017). An innovative framework for building agency-free credit rating systems. *IEEE 10th International Conference on Service-Oriented Computing and Applications* (pp. 181–189). Taiwan: IEEE.
- Chen, -C.-C., & Li, S.-T. (2014). Credit rating with a monotonicity-constrained support vector machine model. *Expert Systems with Applications*, 41(16), 7235–7247. November 15. <https://doi.org/10.1016/j.eswa.2014.05.035>
- Chen, N., Vieira, A., Ribeiro, B., & Duarte, J. M. (2011). A stable credit rating model based on learning vector quantization. *Intelligent Data Analysis*, 15(2), 237–250. <https://doi.org/10.3233/IDA-2010-0465>
- Chi, G., & Meng, B. (2019). Debt rating model based on default identification Empirical evidence from Chinese small industrial enterprises. *Management Decision*, 57(9), 2239–2260. <https://doi.org/10.1108/MD-11-2017-1109>

- Cho, H., & Choi, S. (2015). what drives credit rating changes? A return decomposition approach. *Asia-Pacific Journal of Financial Studies*, 44(6), 899–931. December 1. <https://doi.org/10.1111/ajfs.12118>
- Cubas-Diaz,, & Sedano. (2018). Do credit ratings take into account the sustainability performance of companies? *Sustainability*, 10(11), 1–24. November. <https://doi.org/10.3390/su10114272>
- Daskalopoulos, E., Evgenidis, A., Tsagkanos, A., & Siriopoulos, C. (2016). Assessing variations in foreign direct investments under international financial reporting standards (IFRS) adoption, macro-socioeconomic developments and credit ratings. *Investment Management and Financial Innovations*, 13(3), 328–340. October 10. [https://doi.org/10.21511/imfi.13\(3-2\).2016.05](https://doi.org/10.21511/imfi.13(3-2).2016.05)
- Ding, S., Ma, Y., & Zhou, H. (2019). Implementation of dynamic credit rating method based on clustering and classification technology. *Cluster Computing*, 22(1), 13711–13721. <https://doi.org/10.1007/s10586-018-2076-4>
- Dos Reis, G., Pfeuffer, M., & Smith, G. (2020). Capturing model risk and rating momentum in the estimation of probabilities of default and credit rating migrations. *Quantitative Finance*, 1–15. (April).
- Doumpos, M., & Figueira, J. R. (2019). A multicriteria out-ranking approach for modeling corporate credit ratings: An application of the electre tri-nc method. *Omega*, 82, 166–180. <https://doi.org/10.1016/j.omega.2018.01.003>
- Doumpos, M., Niklis, D., Zopounidis, C., & Andriopoulos, K. (2015, January). Combining accounting data and a structural model for predicting credit ratings: Empirical evidence from European listed firms. *Journal of Banking & Finance*. 50, 599–607, 599–607. <https://doi.org/10.1016/j.jbankfin.2014.01.010>
- Dwivedi, P. K., & Tripathi, S. P. (2019). A simplified interval type-2 fuzzy implementation for financial credit decision. *International Journal of Innovative Technology and Exploring Engineering*. 8(10), 3036–3044. DOI: 10.35940/ijitee.J9478.0881019
- Edmund, A. D., Powell, R., & Singh, A. K. (2013). A dynamic credit ratings model. *20th International Congress on Modelling and Simulation, MODSIM* (pp. 1291–1297). Australia: Elsevier.
- El-Masry, A. A. (2016). Capital structure and performance of Middle East and North Africa (MENA) banks: An assessment of credit rating. *Banks and Bank Systems*, 11(1), 77–91. April 25. [https://doi.org/10.21511/bbs.11\(1\).2016.09](https://doi.org/10.21511/bbs.11(1).2016.09)
- Estevez, P. G., & Carballo, A. (2015). Qualitative judgement in public credit ratings: A proposed supporting approach using Self-Organising Maps (SOMs). *Cuadernos de Economía*, 38(108), 181–190. <https://doi.org/10.1016/j.cesjef.2015.07.003>
- Evgenidis, A., Daskalopoulos, E., Tsagkanos, A., & Siriopoulos, C. (2016). Assessing variations in foreign direct investments under international financial reporting standards (IFRS) adoption, macro-socioeconomic developments and credit ratings. *Investment Management and Financial Innovations*, 3(2), 328–341. <https://ssrn.com/abstract=2864152>
- Fan, M., Yang, S., & Zhang, J. (2008). Credit rating models considering sample selection biases. *International Seminar on Business and Information Management* (pp. 433–436). Wuhan: IEEE.
- Fieberg, C., Mertens, R. L., & Poddig, T. (2016). The relevance of credit ratings over the business cycle. *Journal of Risk Finance*, 17(2), 152–168. March 21. <https://doi.org/10.1108/JRF-08-2015-0079>
- Florian, K. (2016). Spring). do investors still rely on credit rating agencies? Evidence from the financial crisis. *Journal of Fixed Income*, 25(4), 20–31. <https://doi.org/10.3905/jfi.2016.25.4.020>
- FourieI, E., VersterI, T., & Vuuren, G. W. (2016). A proposed quantitative credit-rating methodology for South African provincial departments. *South African Journal of Economic and Management Sciences*, 19(2), 192–214. June. <https://doi.org/10.4102/sajems.v19i2.1260>
- Gavalas, D., & Syriopoulos, T. (2014). An integrated credit rating and loan quality model: Application to bank shipping finance. *Maritime Policy & Management*. 42(6), 1–22. DOI: 10.1080/03088839.2014.904948
- Gong, M. (2017). Research and application of credit rating model in small and micro enterprises based on fuzzy neural network. *Journal of Discrete Mathematical Sciences and Cryptography*, 20(4), 817–834. MAY. <https://doi.org/10.1080/09720529.2017.1364042>
- Guo, X., Zhu, Z., & Shi, J. (2012). A corporate credit rating model using support vector domain combined with fuzzy clustering algorithm. *Mathematical Problems in Engineering*, 1(2).
- Guotai, C., & Zhipeng, Z. (2017). Multi criteria credit rating model for small enterprise using a nonparametric method. *Sustainability*, 01–23. (October 12).
- Habachi, M., & Benbachir, S. (2019). Combination of linear discriminant analysis and expert opinion for the construction of credit rating models: The case of SMEs. *Cogent Business & Management*, 6(1), 1–34. <https://doi.org/10.1080/23311975.2019.1685926>
- Han, S. H., & Reinhart, W. (2018). Influence of global versus local rating agencies to Japanese financial firms. *The Journal of Asian Finance, Economics and Business*, 5(4), 9–20. October. <https://doi.org/10.13106/jafeb.2018.vol5.no4.9>
- Hongxia, W., Xueqin, L., & Yanhui, L. (2010). Enterprise credit rating model based on fuzzy clustering and decision tree. *3rd International Symposium on Information Science and Engineering*, (pp. 105–108). China.
- Hristova, D., Probst, J., & Eckrich, E. (2017). RatingBot: A text mining based rating approach. *Thirty Eighth International Conference on Information Systems*. 8, pp. 1–20. South Korea: Association for Information Systems.
- Hsu, C. F., & Hung, H.-F. (2009). Classification methods of credit rating - A comparative analysis on SVM, MDA and RST. *2009 International Conference on Computational Intelligence and Software Engineering* (pp. 01–04). Wuhan: IEEE.
- Hsu-Che, W., Ya-Han, H., & Yen-Hao, H. (2014). Two stage credit rating prediction using machine learning techniques. *Kybernetes*, 43(7), 1098–1113. <https://doi.org/10.1108/K-10-2013-0218>
- Huang, Z., Chen, H., Hsu, C., Chen, W., & Wu, S. (2004). Credit rating analysis with support vector machines and neural networks: A market comparative study. *Decision Support Systems*, 37(4), 543–558. [https://doi.org/10.1016/S0167-9236\(03\)00086-1](https://doi.org/10.1016/S0167-9236(03)00086-1)
- Huck, N. (2019). Large data sets and machine learning: Applications to statistical arbitrage. *Uropean Journal of Operational Research*, 278(1), 330–342. <https://doi.org/10.1016/j.ejor.2019.04.013>
- Iyengar, S. (2012). The credit rating agencies – are they reliable? A study of sovereign ratings. *Vikalp*, 32(1), 69–82. January. <https://doi.org/10.1177/0256090920120106>
- Jiang, G. (2007). Research on credit rating method based on BP NN. *International Conference on Service Systems and Service Management*. China.



- Josephsona, J., & Shapiro, J. (2020). Credit ratings and structured finance. *Journal of Financial Intermediation*, 40, 1–15.
- Ju, Y., & Sohn, S. Y. (2017). Technology Credit Scoring Based on a Quantification Method. *Sustainability*, 9 (1057), 1–16. <https://doi.org/10.3390/su9061057>
- Kaniovski, Y. M., Boreiko, D. V., & Pflug, G. C. (2016). Numerical modeling of dependent credit rating transitions with asynchronously moving industries. *Computational Economics*, 49(3), 499–516. <https://doi.org/10.1007/s10614-016-9576-1>
- Kao, C., & Wang, C. (2006). A neural based model for financial credit rating of contractors. *International Conference on Engineering Computational Technology*. China.
- Kim, K.-J., & Ahn, H. (2012). A corporate credit rating model using multi-class support vector machines with an ordinal pairwise partitioning approach. *Computers & Operations Research*, 39(8), 1800–1811. <https://doi.org/10.1016/j.cor.2011.06.023>
- Kim, Y., & Sohn, S. Y. (2008). Random effects model for credit rating transitions. *European Journal of Operational Research*, 184(2), 561–573. <https://doi.org/10.1016/j.ejor.2006.12.007>
- Kraus, S., Breier, M., & Dasi-Rodriguez, S. The art of crafting a systematic literature review in entrepreneurship research. (2020). *International Entrepreneurship and Management Journal*, 16(3), 1023–1042. <https://doi.org/10.1007/s11365-020-00635-4>
- Lee, M., Chi, D.-J., & Shen, Z. D. (2010). Applying the hybrid rough set theory and support vector machine in credit rating-consideration of intellectual capital indicator. *ICIC Express Letters*, 4(6), 2255–2260. [http://www.ijcic.org/el-4\(6\)a.htm](http://www.ijcic.org/el-4(6)a.htm)
- Li, B., Li, H., & Gong, M. (2019). Establishment of a mathematical model for enterprise credit risk recognition and rating based on hybrid learning algorithms. *IOP Conference Series Materials Science and Engineering*. 563. China: IOP.
- Li, G., Yang, X., Jun, W., & Tao, Y. (2018). A brief introduction on big data 5Vs characteristics and hadoop technology. *International Conference on Big Data and Education* (pp. 22–26). China: ACM.
- Li, Z., Shuyan, C., & Kun, W. (2013). Chinese Micro-enterprise Credit Rating Model and Empirical Analysis. *Journal of Applied Sciences*, 13(15), 2959–2963. December. <https://doi.org/10.3923/jas.2013.2959.2963>
- Light, R., & Smith, P. (1971). Accumulating Evidence: Procedures for Resolving Contradictions among Different Research Studies. *Harvard Educational Review*, 41(4), 429–471. <https://doi.org/10.17763/haer.41.4.437714870334w144>
- Liu, C., Shi, H., Cai, Y., Shen, S., & Lin, D. (2019). A NEW PRICING APPROACH FOR SME LOANS ISSUED BY COMMERCIAL BANKS BASED ON CREDIT SCORE MAPPING AND ARCHIMEDEAN COPULA SIMULATION. *Journal of Business Economics and Management*, 20(4), 618–632. March. <https://doi.org/10.3846/jbem.2019.9854>
- Lopatta, K., Tchikov, M., & Korner, F. M. (2019). The impact of market sectors and rating agencies on credit ratings: Global evidence. *The Journal of Risk Finance*, 20 (5), 389–410. September 1. <https://doi.org/10.1108/JRF-09-2017-0145>
- Machek, O., & Hnilica, J. (2013). A Stochastic Model of Corporate Lifespan Based on Corporate Credit Ratings. *International Journal of Engineering Business Management*, 5(45), 1–8. August 17. <https://doi.org/10.5772/56918>
- Merriam Webster. (2020, April 24). Merriam Webster: <https://www.merriam-webster.com/dictionary/credit%20rating>
- Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29 (2), 449–470. <https://doi.org/10.1111/j.1540-6261.1974.tb03058.x>
- Michael, D., & Constantin, Z. (2011). A multicriteria out-ranking modeling approach for credit rating. *Decision Sciences*, 42(3), 721–742. July. <https://doi.org/10.1111/j.1540-5915.2011.00328.x>
- Mileris, R., & Boguslauskas, V. (2011). Credit risk estimation model development process: Main steps and model improvement. *Engineering Economics*, 22(2), 126–133. <https://doi.org/10.5755/j01.ee.22.2.309>
- Moradi, S., & rafiei, F. M. (2019). A dynamic credit risk assessment model with data mining techniques: Evidence from Iranian banks. *Financial Innovation*, 5(1), 15. March. <https://doi.org/10.1186/s40854-019-0121-9>
- Murphy, A. (2008). An Analysis of the Financial Crisis of 2008: Causes and Solutions. *SSRN Electronic Journal*, 1–28.
- Pasricha, P., Selvamuthu, D., & Arunachalam, V. (2017). Markov regenerative credit rating model. *The Journal of Risk Finance*, 18(3), 311–325. February 10. <https://doi.org/10.1108/JRF-09-2016-0123>
- Paul, J., & Criado, A. R. (2020). The art of writing literature review: What do we know and what do we need to know? *International Business Review*, 29(4), 4. August. <https://doi.org/10.1016/j.ibusrev.2020.101717>
- Pittaway, L., Holt, R., & Broad, J. (2014). Synthesising knowledge in entrepreneurship research: The role of systematic literature reviews. In *Handbook of research on small business and entrepreneurship*. Edward Elgar.
- Polito, V., & Wickens, M. (2014). Modelling the U.S. sovereign credit rating. *Journal of Banking & Finance*, 46(1), 202–218. <https://doi.org/10.1016/j.jbankfin.2014.05.008>
- Qiu, W. (2019, July). Credit risk prediction in an imbalanced social lending environment based on XGBoost. *5th International Conference on Big Data and Information Analytics* (pp. 150–156). China: IEEE.
- Raghunathan, V., & Varma, J. (1992). CRISIL Ratings: When does AAA means B? *Vikalpa*, 17(2), 35–42. June April. <https://doi.org/10.1177/0256090919920204>
- Rebryk, M., Rebryk, Y., Sokol, S., & Kozmenko, Y. (2017). The potential of conflicts of interest arising in the activities of credit rating agencies in Ukraine. *Problems and Perspectives in Management*, 15(2), 222–233. July 18. [https://doi.org/10.21511/ppm.15\(2-1\).2017.06](https://doi.org/10.21511/ppm.15(2-1).2017.06)
- Reis, G. D., Pfeuffer, M., & Smith, G. (2020, April). Capturing model risk and rating momentum in the estimation of probabilities of default and creditrating migrations. *Quantitative Finance*. 1–16.
- Rogers, D., Mendes-da-Silva, W., & Rogers, P. (2016, June 13). Credit Rating Change and Capital Structure in Latin America. 13(2), 1–22.
- Rudden, R. (2015). *Evolution of Credit Ratings*. Caribbean Information and Credit Rating Service Limited.
- Sangiorgi, F., & Spatt, C. (2017). The Economics of Credit Rating Agencies. *Foundations and Trends in Finance*, 12(1), 1–116. <https://doi.org/10.1561/05000000048>
- Satchidananda, S. S., Panikar, R. B., & Pradeep (2007, July). Credit rating model for rural borrowers. *Innovative Applications of Information Technology for the Developing World* (pp. 185–196). Nepal: World Scientific.
- Shi, B., BinMeng,, & Wang, J. (2016). An optimal decision assessment model based on the acceptable maximum LGD of commercial banks and its application. *Scientific Programming*, 01–09.
- Shi, B., Zhao, X., Wu, B., & Dong, Y. (2019). Credit rating and microfinance lending decisions based on

- loss given default (LGD). *Finance Research Letters*, 30, 124–129. <https://doi.org/10.1016/j.frl.2019.03.033>
- Shyu, C., & Chi. (2008). Establish credit rating system and apply back-propagation network for forecasting insurance companies. *Innovative Computing Information and Control*. China.
- Taba, N. H., Mousavi, S. K., & Khatavakhohan, A. S. (2019). A novel algorithm developed with integrated metrics for dynamic and smart credit rating of bank customers. *Fundamental Research in Electrical Engineering*, 787–799.
- Taekyu, K., & Injoong, K. (2020). The Influence of Credit Scores on Dividend Policy: Evidence from the Korean Market. *Journal of Asian Finance Economics and Business*, 7(2), 33–42. February. <https://doi.org/10.13106/jafeb.2020.vol7.no2.33>
- Tanja, V., Riaan, D. J., & Simon, G. (2019). A motivation for banks in emerging economies to adapt agency ratings when assessing corporate credit. *South African Journal of Economic and Management Sciences*, 22(1), 1–11. <http://dx.doi.org/10.4102/sajems.v22i1.2818>
- Thomas, L. C. (2000). A survey of credit and behavioural scoring: Forecasting financial risk of lending to consumers. *International Journal of Forecasting*, 16(2), 149–172. [https://doi.org/10.1016/S0169-2070\(00\)00034-0](https://doi.org/10.1016/S0169-2070(00)00034-0)
- Tounsi, Y., Hassouni, L., & Anoun, H. (2018). An enhanced comparative assessment of ensemble learning for credit scoring. *International Journal of Machine Learning and Computing*, 8(5), 409–415. DOI: [10.18178/ijmlc.2018.8.5.721](https://doi.org/10.18178/ijmlc.2018.8.5.721)
- Ven, R. V., Dabadghao, S., & Chockalingam, A. (2018, November 19). Assigning Eurozone sovereign credit ratings using CDS spreads. *Journal of Risk Finance*, 19(5), 478–512. <https://doi.org/10.1108/JRF-06-2017-0096>
- Venkiteshwaran, V. (2014). Do asset sales affect firm credit risk? – Evidence from credit rating assignments. *Managerial Finance*, 40(9), 903–927. <https://doi.org/10.1108/MF-09-2012-0196>
- Vyacheslav, B. (2019). Pax RusSinica: On the probability of the formation of a Russian–Chinese strategic alliance on the Eurasian continent. In E. Safronova (Ed.), *China in World and Regional Politics: History and Modernity* (Vol. 24, pp. 80–97). Brill.
- Wang, X., Xu, M., & Pustatli, T. A. (2015). A survey of applying machine learning techniques for credit rating: Existing models and open issues. *Neural Information Processing*, 9490, 122–132.
- Webster, J., & Watson, R. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly*, 26(2), 13–23. <http://www.jstor.org/stable/4132319>
- Wei, Y., Xu, S., & Meng, F. (2010). The listed company's credit rating based on logistic regression model add non-financial factors. *2010 Second International Conference on Modeling, Simulation and Visualization Methods* (pp. 172–175). China: IEEE.
- White, L. (2013). Credit rating agencies: An overview. *Annual Review of Financial Economics*, pp. 93–122.
- Wickens, M. (2016). The eurozone financial crisis: Debt, credit ratings and monetary and fiscal policy. *Empirica*, 43(2), 219–233. April 19. <https://doi.org/10.1007/s10663-016-9335-5>
- Wiener-Ferhofer, A. (2017). Credit rating process A distinction between family and non-family firms regarding their rating score. *Journal of Family Business*, 7(3), 256–290. August. <https://doi.org/10.1108/JFBM-06-2017-0013>
- Wu, H.-C., & Wu, Y.-T. (2016). Evaluating credit rating prediction by using the KMV model and random forest. *Kybernetes-The International Journal of Cybernetics, Systems and Management Sciences*, 45(10), 1637–1651. November. <https://doi.org/10.1108/K-12-2014-0285>
- Wu, Y., Yang, M., & Chen, K. (2016). Research on the credit rating model of energy contract management mode in power grid enterprises. *International Conference on Material Science and Environmental Engineering*, (pp. 807–812). China.
- Xu, L., & Zhang, Y. (2017). A credit rating model for online P2P lending based on analytic hierarchy process. *Tenth International Conference on Management Science and Engineering Management*. 502, pp. 537–549. China: Springer.
- Yeh, -C.-C., Lin, F., & Hsu, C.-Y. (2012). A hybrid KMV model, random forests and rough set theory approach for credit rating. *Knowledge-Based Systems*, 33, 166–172. September. <https://doi.org/10.1016/j.knosys.2012.04.004>
- Yoshino, N., & Taghizadeh-Hesary, F. (2015). Analysis of credit ratings for small and medium-sized enterprises: Evidence from Asia. *Asian Development Review*, 32(2), 18–37. September. [https://doi.org/10.1162/ADEV\\_a\\_00050](https://doi.org/10.1162/ADEV_a_00050)
- Yu, S., Chi, G., & Jiang, X. (2018). Credit rating system for small businesses using the K-S test to select an indicator system. *Management Decision*, 57(1), 229–247. June. <https://doi.org/10.1108/MD-06-2017-0553>
- Zhang, D., & Zhang, Q. (2004). Enterprise credit rating model based on neural networks. *Beijing Ligong Daxue Xuebao/Transaction of Beijing Institute of Technology*, 24(11), 982–985.
- Zhang, L., Hu, H., & Zhang, D. (2015). A credit risk assessment model based on SVM for small and medium enterprises in supply chain finance. *Financial Innovation*, 1–21.
- Zhang, Y., & Chi, G. (2018). A credit rating model based on a customer number bell-shaped distribution. *Management Decision*, 56(5), 987–1007. May 14. <https://doi.org/10.1108/MD-03-2017-0232>
- Zhao, Q. (2017). Do managers manipulate earnings to influence credit rating agencies' decisions? Evidence from watchlist. *Review of Accounting and Finance*, 16(3), 366–384. August 14. <https://doi.org/10.1108/RAF-05-2016-0078>





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