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Published Version:
Cosma, S., Rimo, G., Torluccio, G. (2023). Knowledge mapping of model risk in banking. INTERNATIONAL REVIEW OF FINANCIAL ANALYSIS, 89, 1-15 [10.1016/j.irfa.2023.102800].

Availability:
This version is available at: https://hdl.handle.net/11585/942873 since: 2024-06-27

Published:
DOI: http://doi.org/10.1016/j.irfa.2023.102800

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1 Introduction

For some years, model risk has become a factor that financial institutions must consider in addition to traditional risks, such as credit risk or operational risk (Yang et al., 2011). It represents the potential for adverse consequences of decisions based on incorrect or misused model results and reports. Model risk can lead to financial losses, poor business and strategic decisions or damage to a bank's reputation (Federal Reserve, 2011).

Identifying model risk first requires an understanding of what is meant by a model. A model is defined by the Federal Reserve as a quantitative method, system or approach that applies statistical, economic, financial or mathematical theories, techniques and assumptions to process input data into quantitative estimates. These models can be used to analyze business strategies, identify and measure risks, evaluate exposures, perform stress tests and so on. As such models are simplified representations of complex dynamics, they are therefore prone to a degree of 'model risk' (Panman et al., 2019).

To date, banks increasingly use decision models in their risk management processes at the loan origination, collection and loan restructuring stages to meet regulatory requirements such as capital raising and credit stress testing or to perform scenario analysis (Ali & Daly, 2010). In the commercial area of institutions, models are used to perform real-time matching between customer preferences and product features and to perform customer retention and engagement actions at all stages of the relationship with the bank and for the correct pricing of products or for activities related to anti-money laundering and fraud detection, also thanks to the introduction of big data. Finally, models have always been used by banks in derivatives trading, which relies heavily on theoretical models for pricing contracts and assessing and hedging risk (Green & Figlewski, 1999).

Another area where models are widely used is accounting. IFRS 13 introduces a fair value hierarchy based on the degree of observability of the valuation techniques used to measure underlying assets/liabilities. Specifically, the hierarchy categorizes the inputs required to estimate FV into market-based (Level 1), indirectly observable (Level 2) and model-based (Level 3) assets (Filip et al. 2021). For Level 3 assets, fair value is calculated based on valuation models that mainly use inputs that are not observable in active markets. The unobservable parameters that can influence the valuation of instruments classified as Level 3 are mainly represented by estimates and assumptions underlying the valuation models. This results in these assets/liabilities being exposed to a strong model risk.

The increase in model risk among emerging risks is related to the strong increase in the use of models as a decision support tool for companies, but also to the regulatory environment. The regulation of market risk in 1996 and the entry into force of Basel II in 2004 allowed banks to use internal models (IRB and AMA) to quantify the regulatory capital held for credit and operational risks (Castermans et al., 2010) to increase the effectiveness of capital requirements (Nickell et al., 2007). Since then, several events have significantly increased the frequency and severity of model risk: financial crises, technological advances and macroeconomic scenario turbulence, including the COVID-19 pandemic. The financial crisis of 2007–2009 challenged the provisions of the Basel Accord II on capital requirements and VaR model adequacy (Diamandis et al., 2011). It was recognized that the models used to value financial instruments and quantify the risk inherent in portfolios posed significant model risk (Kiesel et al., 2016), and that banks used the IRB approach to manipulate risk weights (Barucci & Milani, 2018). Model-related losses have led regulators to issue new regulations to address the risks arising from inaccurate or inadequate models (Bennet, 2018).

The development of digital technology and the world's entry into the digital age (Jiang et al., 2022) has also impacted models, that have become more complex and less intuitive. In particular, the advent of Industry 4.0 has brought completely new technologies, such as the Internet of Things, cloud computing, big data and analytics, which are driving Fintech innovation, i.e. the combination of financial services and information technology, to automate transactions (Soni et al., 2022). Particularly recent is the application of machine learning and artificial intelligence to financial problems. The financial services sector, taking advantage of technological advances at both the hardware and software levels, increasingly relies on the computational capacity of machines capable of developing complex models that lead to a solid evaluation of new information (Goodell et al., 2021). Banks have started using these techniques to better serve their customers and meet increasingly demanding regulatory requirements (Wall, 2018). Van Liebergen (2017) highlighted the use of machine learning techniques by banks for credit card fraud detection. Machine learning (ML) and artificial intelligence (AI) are increasingly used in pricing, restructuring, and credit decision automation models. Furthermore, the adoption of AI and ML techniques radically transforms trading and investment decisions (Goodell et al., 2021). These techniques, characterized by high complexity, inevitably increase model risk . Although ML models generally perform better predictively than traditional quantitative models, they also pose new challenges in terms of interpretability and stability of forecasts, leading regulators to require rigorous validation phases for both internal and external reporting reasons (Alonso-Robisco & Carbó, 2022; Argyropoulos & Panopoulou, 2019).

The willingness of intergovernmental organizations to address some problems of growing importance, such as environmental degradation and climate change, has led to the launch of projects (e.g. the United Nations SDGs), which, in recent years, have increased companies' awareness towards environmental social governance (ESG) issues (Lim et al., 2022). For the banking sector, ESG factors determine the emergence of new risks to be mapped, monitored and managed. The incorporation of ESG strategies into risk management processes is also a concept recently recalled by the Basel Committee on Banking Supervision (BCBS, 2021). ESG risks are different from traditional banking risks and integrating them into the existing risk management framework poses several challenges, including long time horizons, high uncertainty and lack of data

(Kalfaoglou, 2021). New tools and models for assessing these risks are also required. This represents a new source of model risk for banks.

Finally, the turbulence of the macroeconomic scenarios, including the pandemic COVID -19, showed that not all models were prepared for events or combinations of events and that new events should be included in the stress tests and scenario analyses.

All of the above reasons make model risk particularly relevant and especially necessary for all companies and banks, in particular, to put in place a framework for model risk management and robust regulation in this regard. Although it has always been clear that any model can generate estimation errors or be imperfect, the concept of model risk began to take on a stand-alone status as a risk in 2013, when a clear definition of the same was given with CRD IV. Since then, the literature has also taken more interest in the study of model risk; the topic is complex, the industry has many issues to resolve, and this requires an in-depth study in this regard.

This study aims to clarify how the topic of model risk in the banking sector has been addressed in the academic literature through a bibliometric investigation to understand state of the art, identify research trends, open questions and challenges for the future. The decision to conduct the study using bibliometric methods was guided by the possibility of identifying new and original fields in which a knowledge gap could be filled (Manesh et al., 2020). To achieve our goal, we address four main research questions (RQs)

RQ1. What are the most cited documents in the field of model risk?

RQ2. What are the most influential journals, authors and countries on this topic?

RQ3: What aspects of model risk have been addressed in the literature?

RQ4: Which questions are still open and require further research and knowledge?

The paper is structured as follows: the second section outlines the basic stages of model risk regulation; the third explains the sample and methodology used, the fourth reports the main findings of the performance analysis, the fifth reports the results of the science mapping, the sixth present a brief review of the most influential and relevant studies in the different thematic clusters identified, and the seventh highlights open questions and challenges for the future. Finally, we report some concluding remarks.

2 The regulation of model risk

At a regulatory level, the first definition of "model risk" is provided by the Federal Reserve in 2011, which within SR 11-7 - Supervisory guidance on model risk management, defines this risk as *the possibility of incurring negative consequences deriving from decisions based on results and reports of incorrect or misused* *models. Model risk can lead to financial losses, poor decision-making and strategic processes, or damage to a bank's reputation*. Model risk occurs mainly for two reasons: a model may have fundamental errors and produce inaccurate results, or the model may be used incorrectly or inappropriately.

With the SR 11-7 regulation, the FED provides guidelines to financial intermediaries on model risk management. It defines a model risk management framework that has not yet been clearly defined in European legislation.

In European legislation, the first definition of model risk is provided in 2013 with the CRD IV, which defines it as *the potential loss that an institution could suffer as a result of decisions that could be mainly based on the results of internal models, due to errors in the development, implementation or use of such models*. It is also established that *competent authorities ensure that institutions implement policies and processes designed to assess and manage exposure to operational risk, which includes model risk, and to cover events of particular gravity and infrequency (EU, 2013).* Therefore, model risk is given importance within the second pillar discipline. This is reiterated in the EBA guidelines on SREP, which include model risk in the II pillar and require banks to identify, map, test and review it on an ongoing basis. Two types of model risk are also defined:

- Risk arising from underestimation of capital requirements by regulatory-approved models (for example, models based on internal ratings-based (IRB) for credit risk);
- The risk of losses resulting from the institution's development, implementation or improper use of other decision models (e.g., product pricing, valuation of financial instruments, monitoring of risk limits, etc.).

For the first type, the EBA requires competent authorities to consider model risk as part of the assessment of specific risks to capital (e.g., IRB model deficit is considered as part of the credit risk assessment) and for the assessment of capital adequacy. For the second type, competent authorities should consider the risk as part of the operational risk assessment. In the same guidelines, the EBA provides that competent authorities should assess the institution's model risk arising from the use of internal models in key operational areas and businesses and, in particular, should assess:

- To what extent and for what purposes (e.g., asset valuation, product pricing, trading strategies, risk management) the institution uses models to make decisions and the importance of those decisions;
- The extent to which the institution is aware of model risk and how the institution manages that risk.

For business lines that make significant use of models, the competent authority should therefore assess how significant the impact of model risk could be, including through sensitivity and scenario analysis or stress testing.

A further contribution is made by the 2017 EBA Guidelines on Internal Governance (EBA / GL / 2017/11), which reinforce the principle that banks must also assess model risk through qualitative approaches, as the results of quantitative assessment methods, including stress testing, are highly dependent on the limitations and assumptions of the models. The definition of responsibilities in the case of models acquired from third parties is clarified. Indeed, the EBA establishes that the ultimate responsibility for risk assessment lies solely with the institution, which consequently should critically assess its risks and not rely solely on external assessments. Therefore, an institution should validate a purchased risk model and adapt it to its circumstances to ensure risk is accurately, comprehensively identified, and analyzed.

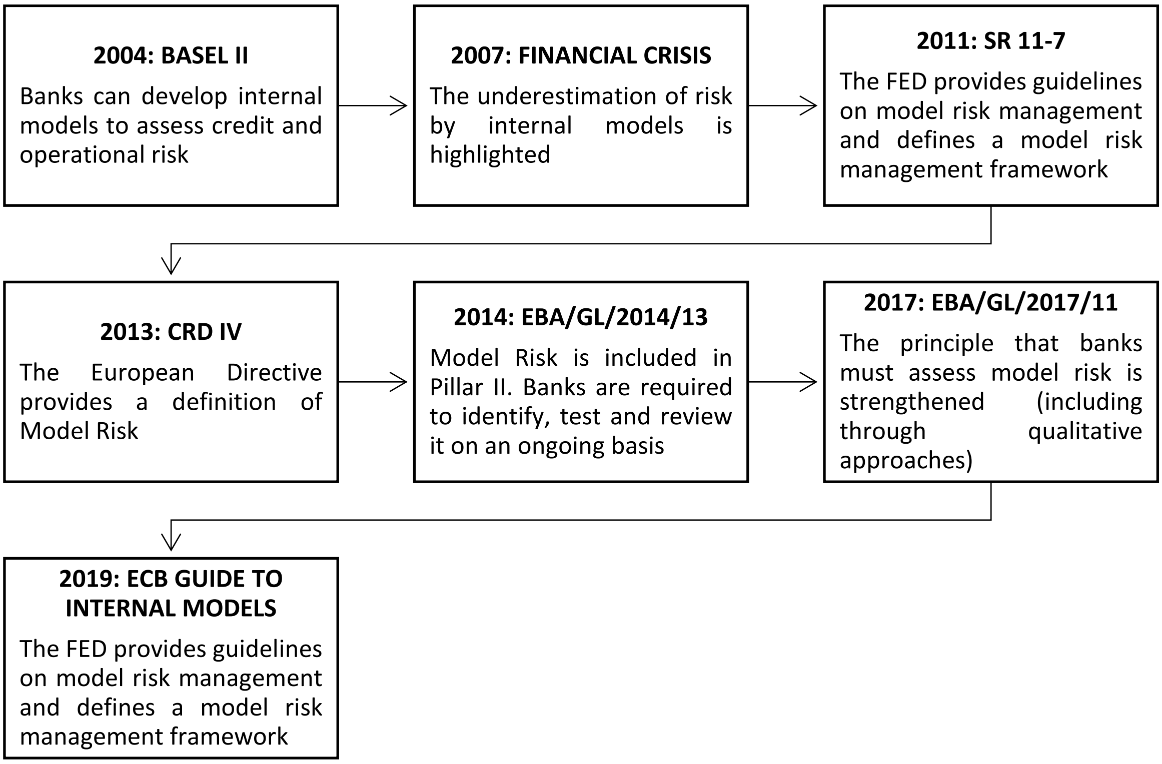
More recently, ECB contributed to model risk management with the publication of the "Guide for the Targeted Review of Internal Models (TRIM)" in February 2017 and the "ECB guide to internal models" in October 2019. First, it states that an institution should have a model risk management framework that enables it to identify, understand and manage its model risk in relation to the group's internal models. This framework should include an inventory of models that enables an understanding of their application and use; guidance on identifying and mitigating areas of known measurement uncertainty and model deficiencies; definitions of roles and responsibilities; and finally, definitions of policies, measurement and reporting procedures. The 2019 document, on the other hand, sets out the basic requirements for an appropriate model risk management framework to reduce the risk of losses or underestimated capital requirements due to model errors. According to the ECB guidance, a model risk management framework should, at a minimum, be characterized by the following features:

- A clearly defined model risk management policy that clarifies what a model is, provides the institution's interpretation of model risk, and describes the model risk framework in terms of its various components (e.g., model governance, risk control function, validation function, internal audit) and associated documented policies.
- A register of the institution's internal models that provides the institution's management body and senior management with a complete overview of the models used.
- Guidelines for identifying and mitigating areas of known existence of models with gaps or measurement uncertainties, based on their relevance. In particular, the focus should be on the qualitative elements of model risk (such as data gaps, misuse of the model, or implementation errors). This methodology should be applied consistently across the Group (e.g., in branches or regions).
- Guidelines and methodologies for qualitative and/or quantitative assessment and measurement of the institution's model risk.
- Guidelines for model life cycle.
- Procedures for communicating and reporting model risks (internally and externally).

- Definition of roles and responsibilities within the model risk management structure (e.g., determining which units are responsible for or involved in the independent review of risk estimates).

Supervisors, therefore, expect institutions to implement a model risk management framework for all models used. The focus is on the transferability of the framework to all areas where the models are used. We are therefore talking about a much more comprehensive framework than a traditional risk management framework.

Figure 1: The rise of model risk as an emerging risk



3 Methodology

3.1 Search protocol

To achieve the research objective of creating a map of scientific studies on model risk in the banking sector, we chose to use Scopus. (Purba et al, 2022; Baker et al, 2021). It represents the database that offers the widest coverage of peer reviewed research in finance and, more generally, in the social sciences (Goodell et al., 2021; Pattnaik et al., 2020). The search was conducted by selecting all studies containing the words "model risk" AND "bank*" OR "financial institution*" OR “financial intermediar*” in the title, abstract, or keywords. The choice to use the term "model risk" derives from the fact that practitioners, regulators and academics have long used it to describe the risks deriving from the incorrect use or incorrect interpretation of statistical, economic, financial or mathematical models. Furthermore, the search string made it possible to extract studies that dealt with the approach of banks to the emerging discipline of model risk management, and to exclude studies that explore model risk from perspectives other than that of banks (e.g., Chalkiadakis et al., 2021).

The first search, carried out on Scopus in January 2023, produced an initial sample of 123 studies published from the beginning to 2023. After that, a dataset cleaning process was carried out: first the source type and English language were selected; we also limited our selection to the end of 2022, the last year with complete data. Then, the titles and abstracts of the articles were read to exclude articles unrelated to the aim of our study. The last phase involved reading the full text of the documents. These screening phases resulted in 101 studies from 1999 to 2022, published on a total of 65 sources. (academic journals, books, conference proceedings). The number of studies analyzed is in line with that of other studies that carry out bibliometric analyses (e.g., Pizzi et al., 2021). Fig. 2 summarizes the research steps that led to data extraction from Scopus.

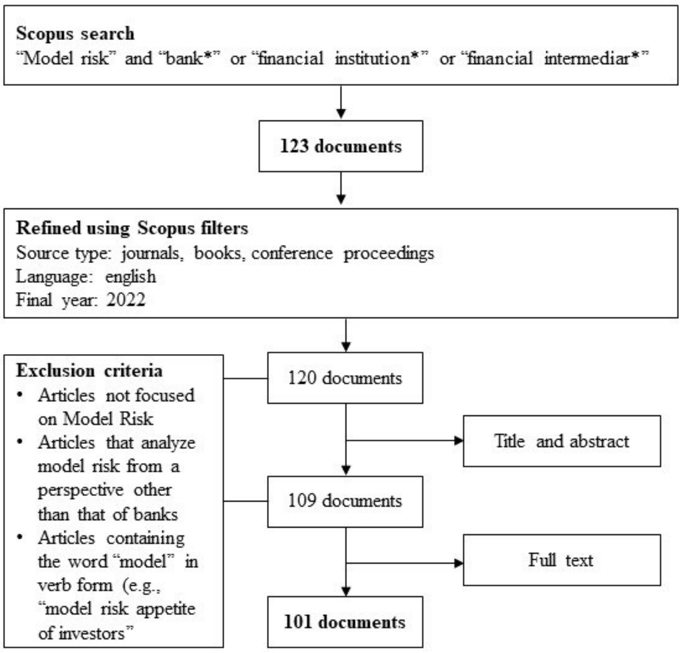


Figure 2: Search and filtration strategy for bibliometric review *(*Our elaboration on the methodological framework proposed by Sureka et al., 2022)

3.2 Bibliometric analysis

The 101 extracted studies were analyzed using the bibliometric research technique, a variant of the systematic literature search (Fan et al., 2022) that involves the application of quantitative and statistical techniques to bibliographic data such as publications and citations (Mukherjee et al., 2022). This type of analysis, which collects a lot of relevant information in a particular field, helps researchers understand the entire framework of a field of study and establish relationships among publications from different subfields (Yue et al., 2021). Using quantitative and statistical data, bibliometric reviews are more objective and comprehensive than other reviews (Donthu et al., 2021).

Bibliometric analysis studies scientific production in a specific research area with the aid of statistical techniques (Broadus, 1987) and usually includes performance analysis and scientific mapping (Donthu et al., 2021). The first type of analysis is based on activity indicators (Mingers & Leydesdorff, 2015) that measure the volume and impact of research through a wide range of techniques, including word frequency analysis and citation analysis. Scientific mapping identifies knowledge clusters in a research area and provides a spatial representation of how different scientific elements relate to each other (Mukherjee et al., 2022; McCain, 1990). In this study, we analyze publication and citation trends, since publication is considered a proxy for productivity, whereas citation is considered a measure of impact and influence (Donthu et al., 2021). This made it possible to identify the most relevant authors, sources, and countries on the subject of model risk in the banking sector (Goodell et al., 2023). In our analysis we also use a co-citation analysis, which measures the affinity between articles, authors, or journals (Cosma et al., 2023). This analysis allowed us to identify the most cited references from the studies of our sample, i.e. the main theoretical pillars that led to the development of the topic.

Then, we scientifically mapped the relationships between publications through keywords. In particular, the co-occurrence of keywords was analyzed to examine the conceptual structure of the field under study based on the authors' keywords (Callon et al., 1983). This analysis examines the actual content of the publication itself, and assumes that if words co-occur in a document, the concepts associated with those words should be related (Donthu et al., 2021). It allows identifying the core themes, the most recent ones and the network of correlations between the topics.

Bibliometrix and VOSViewer software were used to conduct the analysis (Patel et al., 2022; Griffin & Grote, 2020; Bahoo et al., 2020; Raghuram et al., 2019). Specifically, a network visualization was chosen in which elements (keywords) are represented by a marker and a circle whose size varies depending on the relevance of the element itself. The greater the weight of an element (the greater its frequency), the larger the circle. The distance between two elements in the visualization indicates the approximate correlation of the elements with respect to the link metric used (co-occurrence). The different colors and spatial positioning of the circles are used to group the objects. An overlay analysis and a thematic analysis were also used to analyze authors' keywords. The overlay analysis is a graphical evaluation of the authors' keywords which promotes an understanding of the major themes that have been discussed by scientists over the years and can be useful to preview the future of the research field (Casprini et al., 2020, Donthu et al., 2021) The thematic analysis allowed the triangulation of the insights deriving from the study through a thematic map that visualizes the co-occurrence of keywords in clusters distributed over four quadrants on the dimensions of centrality (ie thematic importance) and density (ie thematic development) (Singh et al., 2023).

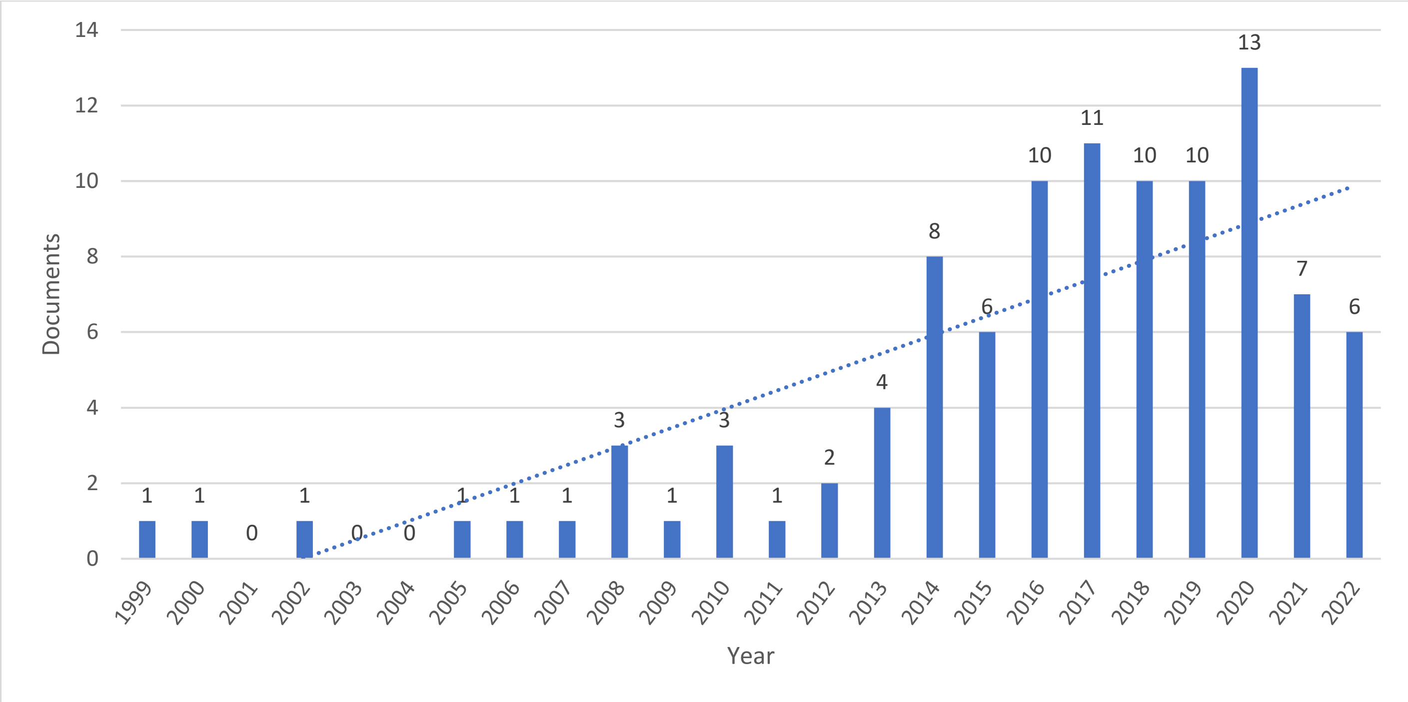
Such visual representations can enhance science communication and facilitate future information retrieval processes, two important foundations of scientific progress (Dinić & Jevremov, 2021).

4 Performance analysis

4.1 Most cited studies and publication patterns

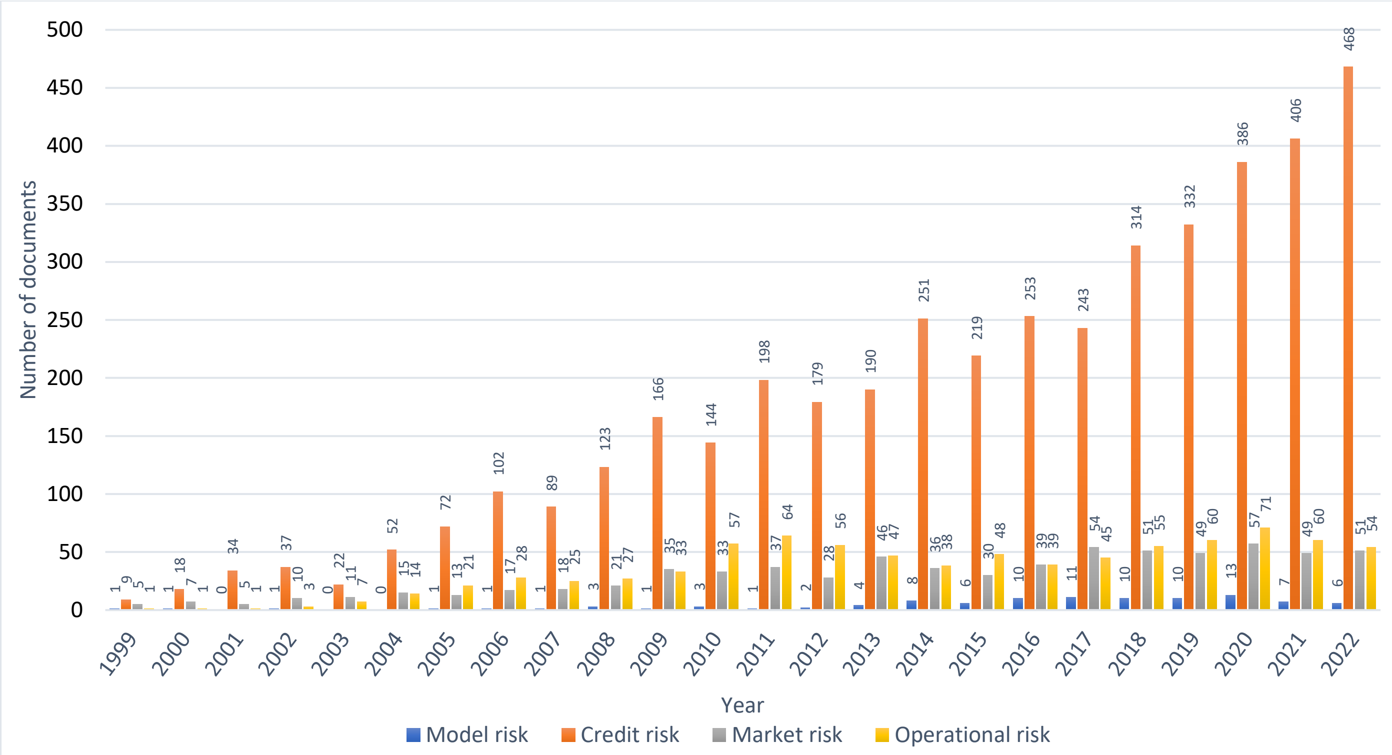
As shown in Figure 3, the scientific production on the topic, according to the data in the database, seems to have developed quite recently, with the first article published in 1999.

Figure 3: Documents per year



Based on the bibliographic data on the literature on banking risk, Figure 4 shows a sharp difference in the volume of academic production on credit risk, market risk, operational risk, and model risk. The literature on the former three risks far outstrips quantitatively the literature on model risk, which is certainly newer and has developed more recently. This is likely due to regulation, which has considered model risk as a subset of operational risk for many years (McKinsey & Company, 2019).

Figure 4: Scientific production on model risk and other banking risks: evolution and volumes



The 101 extracted studies have an average number of citations equal to 10.08 with high variability (st.d. 20.27). Table 1 provides an overview of the most cited articles articles. The citation analysis shows that the most cited article on the topic was published by Wu & Olson (2010), "Enterprise risk management: coping with model risk in a large bank". This paper sheds light on the importance of model risk validation in Enterprise Risk Management in the banking sector. Among the most cited papers we also find that of Green and Figlewski (1999), which highlights the considerable exposure of option writers to model risk resulting from imperfect models and inaccurate volatility forecasts. The third article by number of citations is that of Gauthier et al. (2012). The authors discuss the need to orient banking regulation towards a systemic perspective, investigating possible regulatory requirements robust to the model risk that force a bank to internalize some of the externalities it creates for the banking system and therefore to reduce the endogenous risk created in the financial system.

Table 1: Most cited studies

TC	Title	Authors	Source title	Year
114	Enterprise risk management: Coping with model risk in a large bank	Wu D., Olson D.L.	Journal of the Operational Research Society	2010
100	Market risk and model risk for a financial institution writing options	Green T.C., Figlewski S.	Journal of Finance	1999
99	Macroprudential capital requirements and systemic risk	Gauthier C., Lehar A., Souissi M.	Journal of Financial Intermediation	2012
69	Supervisors as information producers: Do stress tests reduce bank opaqueness?	Petrella G., Resti A.	Journal of Banking and Finance	2013
57	Model risk and capital reserves	Kerkhof J., Melenberg B., Schumacher H.	Journal of Banking and Finance	2010

56	Risk models-at-risk	Boucher C.M., Daníelsson J., Kouontchou P.S., Maillet B.B.	Journal of Banking and Finance	2014
45	Quantile Uncertainty and Value-at-Risk Model Risk	Alexander C., Sarabia J.M.	Risk Analysis	2012
33	Comparison of selected methods for performance evaluation of Czech and Slovak commercial banks	Gavurova B., Belas J., Kocisova K., Kliestik T.	Journal of Business Economics and Management	2017
31	The information in systemic risk rankings	Nucera F., Schwaab B., Koopman S.J., Lucas A.	Journal of Empirical Finance	2016
28	Quantifying market risk with Value-at-Risk or Expected Shortfall? - Consequences for capital requirements and model risk	Kellner R., Rösch D.	Journal of Economic Dynamics and Control	2016
27	Does a leverage ratio requirement increase bank stability?	Kiema, I., Jokivuolle, E.	Journal of Banking and Finance	2014
19	An overview and framework for PD backtesting and benchmarking	Castermans G., Martens D., Gestel T.V., Hamers B., Baesens B.	Journal of the Operational Research Society	2017
16	Bounds on total economic capital: the DNB case study	Aas K., Puccetti G.	Extremes	2010
15	AI lifecycle models need to be revised: An exploratory study in Fintech	Haakman, M., Cruz, L., Huijgens, H., van Deursen, A.	Empirical Software Engineering	2014
14	An analysis of the consistency of banks' internal ratings	Berg, T., Koziol, P.	Journal of Banking and Finance	2021

TC: Total citations

Finally, the co-citation analysis allowed us to identify the theoretical pillars of the studies present in the sample. In particular, among the 3435 total references, the study by Cont (2006) is the most cited. This study addresses the model risk in the valuation of portfolios of options deriving from the uncertainty on the choice of pricing models. The authors introduce a quantitative framework for measuring model risk in derivative pricing. Among the most cited studies, we also find the paper by Schuermann (2014), which lays out a framework for the stress testing of banks, and the one by Talay and Zheng (2014) which describes the financial strategy that a trader can follow in order to manage his/her model risk. Other studies considered relevant on the subject are that of Kerkhof et al. (2010), which propose a procedure to take model risk into account in the computation of capital reserves, and that of Merton (1974), who developed a method for pricing corporate liabilities.

4.2 Most prolific contributors

This section allows to present an overview of the most prolific and impactful contributors to the field.

By analyzing the sources, we try to trace the scientific journals that have mainly contributed to the development of the topic of model risk in the banking sector. So far, 65 sources in our dataset contain at least one publication on the topic of model risk in the banking sector. 51 of these sources were cited at least once and thus contributed to further research. The average number of citations per journal is 15.17, but with a very high standard deviation (St.d. 37.48), meaning that only a few sources were particularly influential. Table 2 presents the most cited and most prolific sources on the topic of model risk in the banking sector. The citation analysis, which represents a common method to determine the influence and popularity of research in the scientific community (Ding & Cronin, 2011) shows that the highest number of citations (Total Citation - TC) concerns the Journal of Banking and Finance (247), followed by the Journal of the operational research society (132) and the Journal of financial intermediation (100). Among the most prolific sources we find Journal of Risk Model Validation, Journal of Banking And Finance and Journal of Risk Management In Financial Institutions.

Table 2
Most prolific and most cited sources in model risk research

Most cited sources		Most prolific sources	
Source	TC	Source	TP
Journal of Banking and Finance	247	Journal of Risk Model Validation	10
Journal of The Operational Research Society	132	Journal of Banking And Finance	7
Journal of Financial Intermediation	100	Journal of Risk Management In Financial Institutions	5
Journal of Finance	99	Journal of Operational Risk	4
Risk Analysis	45	Journal of The Operational Research Society	3
Journal of Business Economics and Management	33	Journal of Risk	3
Journal of Empirical Finance	31	Springer Proceedings in Business and Economics	3
Journal of Economic Dynamics and Control	28	International Journal of Theoretical and Applied Finance	2
Journal of Risk Model Validation	25	Risks	2
Integrated Environmental Assessment and Management	21	Journal of Credit Risk	2
International Journal of Theoretical and Applied Finance	19	Journal of Banking Regulation	2
Extremes	16	Risk Management	2
Empirical Software Engineering	15	Journal of Economics and Finance	2

TP: Total publications; TC: Total citations

Table 3 presents the most prolific and most cited countries on the topic. The United States is the country with the most publications (22), followed by the United Kingdom (21) and Germany (12). Furthermore, the United States emerges as the most cited country (313). We also find Canada, the United Kingdom and Italy among the most cited countries.

Table 3
Most prolific and impactful countries in model risk research

Most cited countries		Most prolific countries	
Source	TC	Source	TP
United States	313	United States	22
Canada	214	United Kingdom	21
United Kingdom	162	Germany	12
Italy	122	France	8
Germany	118	Italy	6

Russian Federation	107	Switzerland	6
Netherlands	103	Canada	5
Belgium	76	South Africa	5
France	69	Spain	5
Spain	53	China	4
Czech Republic	33	Netherlands	3
Slovakia	33	Taiwan	3
Denmark	31	Belgium	2
Finland	27	Denmark	2
Norway	26	Greece	2
Norway	2	Switzerland	22
Poland	2	Austria	10

TP: Total publications; TC: Total citations

The sample of articles considered shows the presence of 227 authors who have contributed to the development of research on model risk in the financial sector. Of them, 36 have received at least 20 citations. The average number of citations per author is 11.77, with a high variation compared to the average (St.d. 21.47). Table 4 presents the most prolific and most cited authors on the topic. Based on the citation analysis, we can identify the two authors who have the highest number of citations (TC) and thus are the most important and widely read on the studied topic, namely Wu from the University of Chinese Academy of Sciences, School of Economics and Management, and Olson from the University of Nebraska, Department of Management. Among the most prolific authors, we find Jacobs (The PNC Financial Services Group, Inc.), and Tunaru (University of Sussex Business School), with three publications each.

Table 4
Most prolific and most cited authors in model risk research

Most cited authors		Most prolific authors	
Author	TC	Author	TP
Wu D.	119	Jacobs M.	3
Olson D.L.	132	Tunaru R.	3
Gauthier C.	113	Alexander C.	2
Lehar A.	100	Fischer M.	2
Souissi M.	100	Haasbroek L.J.	2
Figlewski S.	99	Jakob K.	2
Green T.C.	99	Krajčovičová Z.	2
Petrella G.	69	Mashele H.P.	2
Resti A.	69	Olson D. L.	2
Kerkhof J.	57	Papadopoulos G.	2
Melenberg B.	57	Pérez-Velasco P.P.	2
Schumacher H.	57	Seitshiro M.B.	2
Boucher C.M.	56	Vázquez C.	2
Danielsson J.	56	Verster T.	2
Kountchou P.S.	56	Wied D.	2
Maillet B.B.	56	Wu D.	2
Alexander C.	51	Ziggel D.	2

TP: Total publications; TC: Total citations

5 Science mapping

5.1 Network analysis

Science mapping is fundamental to identifying the thematic areas that constitute the theoretical building blocks or foundational arguments for the field under study (Manesh et al., 2020). The analysis of the co-occurrence of the keywords is presented in a network diagram showing the network of keywords (Figure 5). This diagram shows three clusters in the research field under study:

- First cluster (red): It is characterized by studies dealing with regulation, capital requirements, and a macroprudential or systemic view of model risk.
- Second cluster (blue): This research area contains several studies that focus on the management of model risk and its impact on credit risk with a microprudential or firm-level view.
- Third cluster (green): Contains studies that focus on the application of new technologies in the area of model risk, with a more innovative focus on model governance.

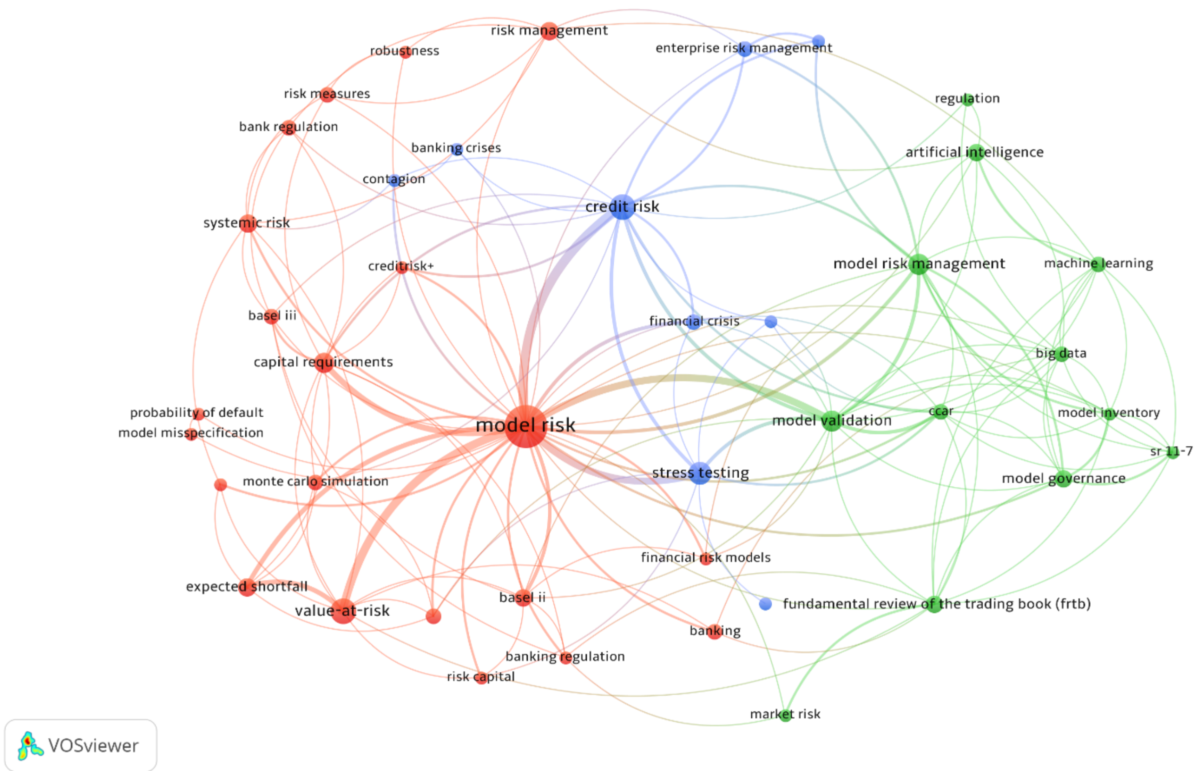


Figure 5: Network diagram of the co-occurrence of keywords

5.2 Overlay analysis

Overlay analysis allows determining the temporal distribution of keywords contained in each cluster (Figure 6). The keywords can be arranged on a timeline with the oldest and most profound research topics and the emerging topics whose treatment has only developed in recent years. In the diagram, the keywords are colored based on a score. This score is assigned based on the average year in which a keyword appeared. The colors range from blue (more distant years) to green and yellow (more recent). From the map, we can infer that model risk was originally a measurement problem associated with value at risk and expected shortfall and was analyzed as part of operational risk studies. Subsequently, model risk takes on a value of its own and establishes itself as a risk to be considered in the calculation of capital. It is associated with macroprudential studies and regulation. The studies, therefore, move to the management of model risk and to this risk in the context of the stress testing and validation phases, and then examine how new technological innovations, big data, ML and AI, can improve the management of this risk.

The map shows that the most discussed topics in the last two years are precisely those that belong to the green cluster identified by the network diagram, i.e. ML, big data, AI and, more generally, digitalization. These arguments are intertwined with model risk in two ways. On the one hand, artificial intelligence tools may be increasingly used in model validation, likely going beyond the scope of statistical testing and intercepting elements of documentary analysis and reporting; on the other hand, the emergence of new AI and ML techniques may represents a new model risk factor requiring specific assessment and measurement tools and techniques. In this context, the contribution of academics and practitioners can play a crucial role in deepening the methodology discussion by extending it to other approaches to model risk measurement and providing it with use case studies.

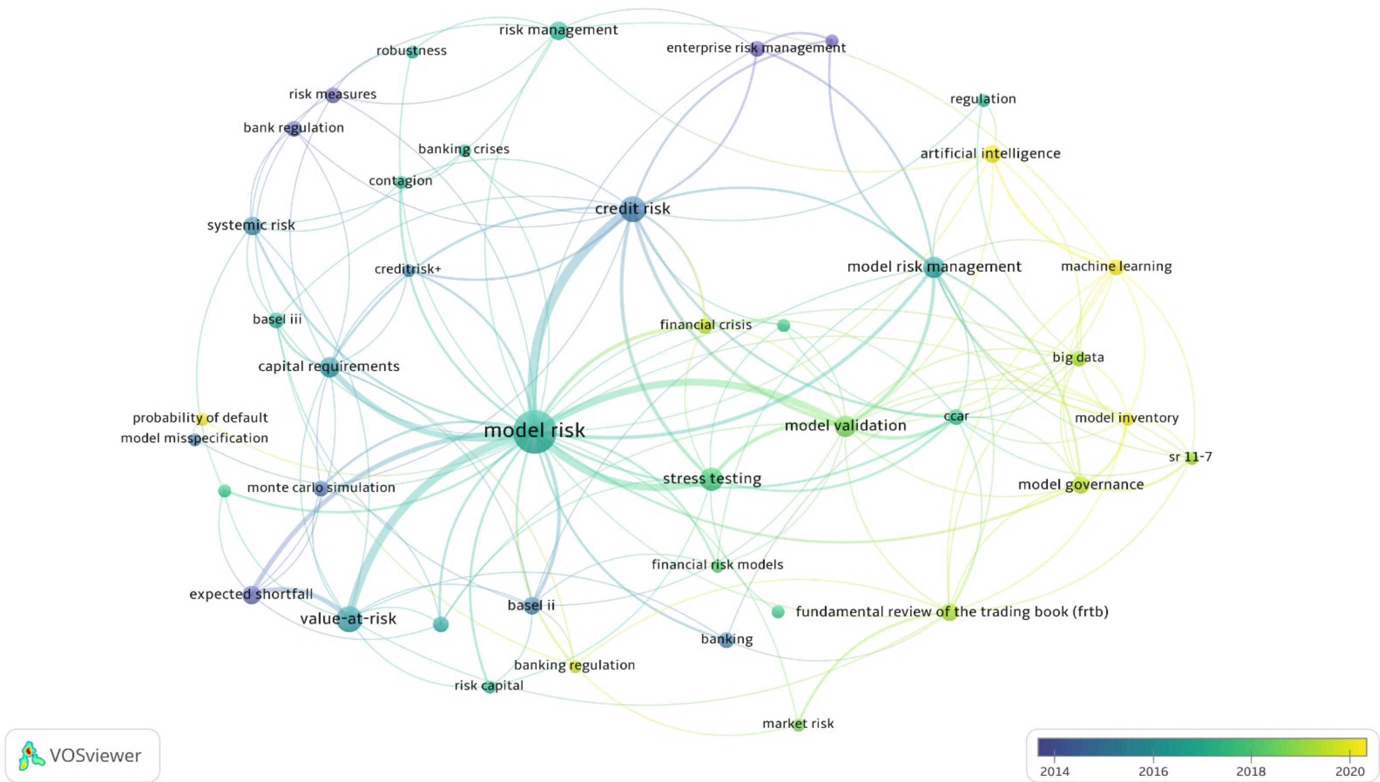


Figure 6: Overlay analysis.

5.3 *Thematic analysis*

In this study we also used Bibliometrix R to perform a *thematic analysis* on the co-occurrence of keywords in publications on model risk in banking studies. Using another software allowed for a robustness test, as recommended by several previous studies, and favors the triangulation of cluster insights (Goodell et al., 2021). The thematic map visualizes the co-occurrence of keywords in clusters through four quadrants defined on the basis of two dimensions: thematic importance (centrality) and thematic development (density).

On the basis of their positioning, the themes represented are considered "motor themes", i.e. important and developed, if they appear in the upper right quadrant; "niche themes", i.e. developed but isolated, if they appear in the upper left quadrant; "emerging themes", i.e. underdeveloped, in the lower left quadrant; "basic themes", i.e. themes still underdeveloped in the literature but considered important (Singh et al., 2023). The thematic map is shown in Figure 7.

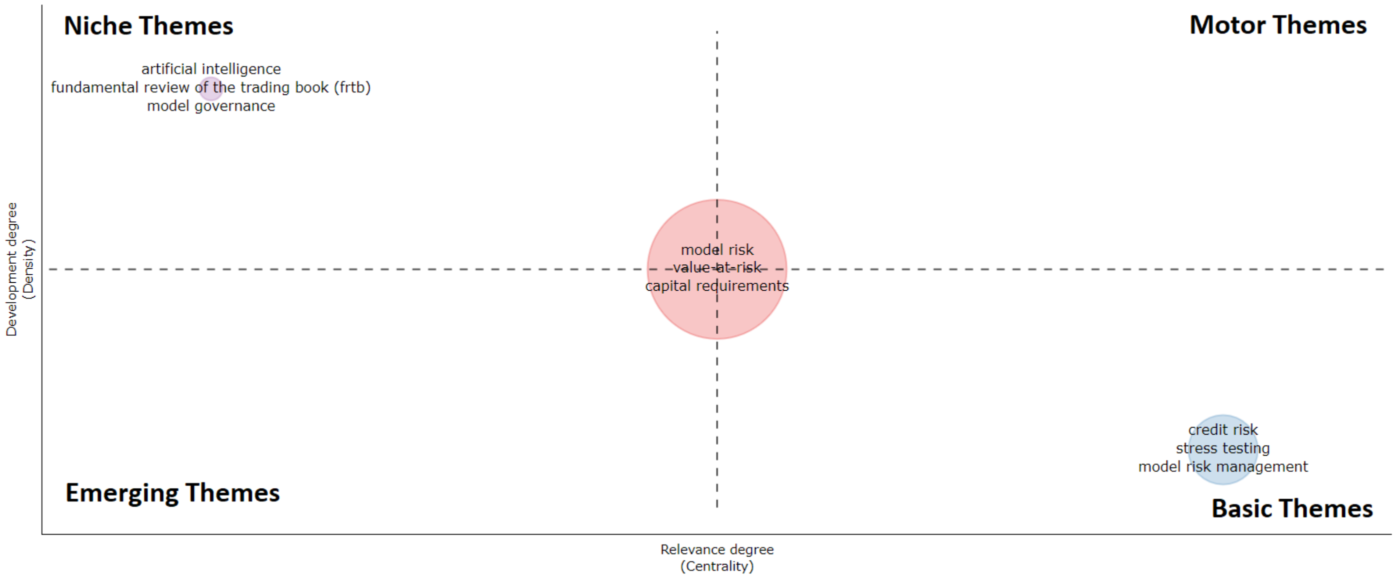


Figure 7: thematic maps of topics

5.4 The thematic map highlights the presence of three main themes, which almost overlap with the three clusters identified in the network diagram in Figure 4: a theme (red circle) on model risk and banking regulation (model risk, value at risk, capital requirements), a theme (blue) on the impact of model risk on credit risk (credit risk, stress testing, model risk management) and, finally, a theme (purple) on emerging technologies and recent changes in banking regulations (artificial intelligence, fundamental review of the trading book, model governance). According to the thematic map, the vision of model risk from a macro-prudential point of view represents a central and dense theme. The issue of the impact of model risk on credit risk appears in the lower right quadrant, described by the analysis as a general issue, therefore important but still underdeveloped. In the upper left quadrant, on the other hand, the themes of emerging technologies and changes in banking regulations appear. These topics appear to be niche, i.e. characterized by a good degree of development, but still rather isolated in the scientific literature. Some first evidence

The integrated reading of the previous figures (5, 6 and 7) allows us to grasp the direct relationship between time and "centrality" of the themes: the less recent studies on the adequacy of capital and its measurement are also those that have an equal level of relevance and interconnection within the model risk debate. Some highly relevant topics are still fragmented (density): the studies concerning the effect of model risk on credit risk, stress testing and aspects of model risk management, developed around 2016, represent thematic areas treated separately and still not well interconnected within the dataset. At the same time, the most recent topics associated with the model risk literature, i.e. the fundamental review of market risk, governance of model risk and the use of new technologies and artificial intelligence systems, represent niche topics, strongly developed but isolated (Singh et al., 2023). The Fundamental review of the trading book has led several academics to analyze the model risk deriving from the new standards relating to capital requirements for market risks in the trading book (Wilkens & Predescu, 2018), as well as to implement new backtesting mechanisms for the 'Expected Shortfall, whose popularity has exploded in recent years (Löser et al., 2018). At the same time, the rapid development of models based on artificial intelligence and their application in the banking sector have given relevance to the problem of model governance (Haakman et al., 2021), which sees new opportunities in the new machine learning systems (Jacobs , 2018; Hill, 2019), but also of the threats to be managed in the same way as traditional banking risks through specific Model Risk Management frameworks (Fritz-Morgenthal et al., 2022; Bennet, 2018; von Thaden & When, 2020). In particular, the most recent issue fueling the debate on model risk is the pervasive use of AI and ML algorithms in banks, generating greater complexity in model risk management as it requires adequate evaluation of the risks associated with the implementation of such algorithms. In particular, the use of AI and ML requires the development of specific validation and control methods that could not always be reflected in the existing skills and competencies, an understanding of model outputs/results which may compromise ensuring model transparency and accountability, and the identification and mitigation of potential biases in the models in order not to affect the impartiality and fairness in the decisions that are made. Finally, Figure 7 highlights the absence of topics with both high centrality and density, i.e. considered at the same time very significant and strongly interconnected, confirming the need to extend the literature on model risk.

6 Thematic clusters: Results

The network analysis (Figure 5) supported the identification of three thematic clusters: a red cluster on model risk and regulation, a blue cluster on model risk and credit risk, and a green cluster on model risk and new technologies. The explanation of the individual clusters takes place through sensemaking, which provides a narration of the research area through an organization of keywords (Donthu et al., 2022) and a brief review of the articles that best characterize the three clusters of knowledge.

6.1 First cluster (red): Model risk and regulation

The red cluster is characterized by studies that deal with 'model risk' from the point of view of 'banking regulation' and highlight the effects of this risk in the calculation of 'capital requirements'. Some studies compare the 'model risk' into 'risk measures', namely the 'value at risk' and the 'expected shortfall' in the scope of market risk, other studies assess the distorting effects of leverage requirements proposed by Basel 3, and still others combine model risk with operational risk by proposing a new taxonomy of events for the latter. Concerning market risk, Kerkhof et al. (2010) expressed concern about the lack of explicit capital requirements related to model risk. This study extends the standard framework for determining market risk by proposing a procedure for considering model risk when calculating capital buffers, which can also be used in combination with any standard risk measure, such as value at risk. The focus is on the model risk associated with uncertainties in econometric modelling. This naturally leads to defining the overall model risk as the sum of three components: estimation risk, misspecification risk and identification risk.

Kellner and Rosh (2016) analyzed the impact of model risk on the 'new' capital requirements given market risk. Indeed, following the publication of the Fundamental Review of the Trading Book in 2013, it is recommended that the expected shortfall ($\alpha = 0.975$) be replaced with the value at risk ($\alpha = 0.99$) to quantify market risk. The study by Kellner and Rosh analyzes the difference between the potential impact of using expected shortfall and value at risk on capital requirements and the associated model risk. Expected shortfall estimates exceed value at risk estimates, thereby increasing capital requirements. However, the expected shortfall is more sensitive to parameter misspecification and regulatory arbitrage and thus to model risk.

Finally, Farkas et al. (2020) proposed a general method to account for model risk when calculating capital requirements related to market risk. In an extensive empirical study focusing on an investment in the S&P 500 stock index, the study examines the extent to which capital requirements for model risk absorb losses in normal and stressed periods. These requirements, determined using the methodology developed by the authors, are then compared to the capital requirements established by the Basel 2.5 accords and the new Basel 4 regulations.

The adjusted capital requirements for model risk perform well in both normal and stress scenarios. They also appear to be very stable over time.

Concerning the leverage ratio requirement (LRR), Kiema and Jokivuolle (2014) examined the impact of the LRR introduced by Basel 3 on lending strategies and its impact on bank stability in light of its purpose, which is to provide a backstop against model risk that could be incorporated into IRB models. Thus, the ultimate goal of the LRR is to provide a stronger capital buffer against the risk of bank risk-weighting errors. However, the LRR penalizes banks that specialize in low-risk loans. They would be tempted to diversify their portfolios into high-risk loans until the LRR was no longer a capital constraint for them. A relatively low LRR, such as the current 3% LRR, could reduce bank stability, contrary to regulatory intentions.

Mérő (2021) highlighted how it became apparent during the crisis that internal models underestimated risk levels. Regulation responded to the financial crisis by introducing constraints on the estimates that banks make with internal models (e.g., output floor at 72.5%). As a result, regulatory policy is less risk sensitive. The study concluded that a mixed regulatory regime between pure risk-based regulation and pure non-risk-sensitive regulation would best mitigate the distortions or disincentives of the two different regulatory regimes.

With respect to operational risk, the growth of model risk has also necessitated a new classification of operational risk, which is still classified based on the event types established by Basel but which have now proven to be outdated. A study conducted by ORX in collaboration with Oliver Wyman (Carrivick et al. 2020) showed that the significant changes in operational risk faced by financial services firms had led banks to review their operational risk taxonomy in recent years. In the absence of a common standard, significant differences were found across institutions. The individual taxonomies of 60 major financial institutions are being brought together to create a new consistent reference taxonomy for operational and nonfinancial risk.

6.2 Second cluster (blue): Model risk and credit risk

The blue cluster is characterized by studies that shed light on the growing relevance of model risk in 'enterprise risk management' in the banking sector. Indeed, 'financial crises' have highlighted various weaknesses in the standard risk models. In the area of 'credit risk', the studies highlight the risks of the models used for the 'stress tests' and for estimating the probability of default.

Among the most cited studies, we find the article by Wu & Olson (2010), which highlights the use of models as a tool to support business decisions, the importance of model risk in enterprise risk management in the banking industry and describes the stages of validating models for credit rating. A large bank's scorecard model was validated and compared with scores from credit bureaus.

Berg and Koziol (2017) examined the reliability of IRB models and their model risk, that is, the possibility of obtaining different estimates of probability of default (PD) from the different internal models. In assessing the consistency of internal PD estimates across banks, the authors show that the variability of PD estimates for the same borrower across banks is significant. Second, bank fixed effects that capture systematic differences in rating models across banks explain 5% of the variation in PD estimates across banks, while 95% are idiosyncratic. In the same research area, an article by Krajčovičová et al. (2019) introduced a general framework for quantifying model risk using differential geometry and information theory and applied the methodology to a PD model used for capital calculations.

Ruiz (2014) examined the backtesting phase of counterparty credit risk (CCR) models. The BCBS requires banks to use the internal model for capital requirements to test the reliability of their models on an ongoing basis, but it does not provide clear guidelines for backtesting counterparty risk models. In his study, Ruiz presented a quantitative methodology for backtesting the above models. Financial institutions can then use this framework to assess model improvement needs and manage model risk. This framework was implemented in one financial institution; the model report was sent to regulators for approval of internal model methods. The model was approved a few months later.

Papadoupulos (2017) focused his study on stress testing for credit risk and showed how a combination of models can lead to better results than if the stress tests were based on a single model. Using a single model to map the impact of macroeconomic shocks on bank-specific risk factors exposes the entire framework to model risk. Any single model can be misspecified and affected by structural changes in ways that are very difficult to predict in advance. The study implemented a combination of models for stress testing credit risk as a remedy.

Finally, Seitshiro and Mashael (2020) identified three sources of model risk: prediction errors in model parameters, misspecified models or improperly implemented models. The authors examined the first case in which model parameters could be estimated with wrong parameter estimators (parameter estimation risk) and attempted to assess model risk for a simple binary logistic regression model used as a predictive model for default probability. The evaluation was done by comparing the effectiveness of 11 different parameter estimation methods and determining the optimal parameters that minimize the cost function of the target model.

6.3 Third cluster (green): Model risk and new technologies

The green cluster is characterized by studies describing the new challenges that the 'model risk management' of banks must face, including those posed by new technologies such as 'artificial intelligence', 'machine learning' and 'big data'. For an appropriate 'model governance' of models based on these technologies, banks must equip themselves with 'model inventory' and special 'model validation' procedures.

In this cluster, the topics of credit risk and stress testing are interwoven by several authors with some forward-looking topics, namely ML, AI, and big data. These tools can help calculate the capital requirements for the risks taken by a financial institution. Still, supporting such technologies depends on the bank's ability to apply them appropriately. In addition to authors who propose methods to mitigate model risk through AI and ML systems, other authors denounce the difficulties banks face in correctly applying these technologies. Among the first is Jacobs (2018), who described the Multivariate Adaptive Regression Splines model (MARS), a machine learning-based model capable of modelling distributions that deviate from the norm to improve the accuracy of traditional stress tests. Among the second, Haakman et al. (2021) highlighted in their study conducted in collaboration with ING that banks do not have much experience in managing ML models and risk assessment teams do not necessarily have a background in machine learning to make informed decisions. Fritz-Morgenthal et al. (2022) discussed, from a regulatory and ethical point of view, all those models used by banks and financial institutions based on AI and ML mechanisms. Typically, such models are used in the value chain of credit risk, insurance risk or other types of financial risk. Models based on AI or ML can be characterized by bias inherent in the training data (outliers, data with incorrect information) or deriving from distortions in the methodology, which could lead to discrimination and reputational problems. To this end, the authors believe that the validation process of these models to control model risk must also verify fairness and the possible presence of unwanted distortions.

In a context made increasingly complex by new disruptive technologies, the role of model risk managers is becoming increasingly important and controversial. Bennet (2018) highlighted the importance of the model risk management (MRM) group in banks, whose role requires political support from the board risk committee. Without this 'tone at the top', it will be difficult for an MRM to fulfil its mandate to independently identify and manage model risk within the organization. Hill (2019) identified 14 challenges faced by model risk managers in a relatively new and evolving discipline and attempted to provide approaches to the challenges posed by the eruption of new technologies in banking, highlighting their pros and cons. ML can be used in model validation processes to assess conceptual soundness, analyze data quality and make basic corrections, such as replacing missing/incorrect data. Big data can provide a huge amount of data that can improve the functionality of current models, such as the models used to calculate the PD. The latter could obtain more accurate forecasts if they had access to demographic data describing the age and geographic distribution of the population combined with income statistics. However, when an ML-based model is used in a validation process, it must itself go through a validation process, which introduces additional complexity. These models are less well known by experts, which makes it difficult to assess their suitability. Sensitivity and backtesting techniques need to be reconsidered for ML models. Similar concerns have also been raised by Von Thaden and When (2020). The authors highlighted the fact that model validation processes, often based on ML and AI, are themselves models and that quantifying model risk very often relies on additional hypotheses leading to infinite regress. In particular, when the validation process itself directly impacts the model or even when model selection is done using nonlinear methods, such as ML, the increase in complexity is enormous, with an analogous impact on the associated model risks. Regarding these considerations, the authors recommend a qualitative assessment of the remaining model uncertainties from a regulatory and supervisory perspective rather than introducing more complexity into the model risk process (von Thaden & When, 2020). Finally, Gan et al. (2021) also pointed to the challenges posed to MRM by the increasing use of AI and proposed a validation test for models based on ML.

7 Discussion

The exposure of banks to model risk is an issue whose importance increases with the introduction of new models, technologies or new applications of existing models into processes. The extensive use of models to support decisions, calculations and strategies makes the ability of the business to manage this risk extremely critical.

The paucity of studies on this topic shows that the literature on model risk is still quite young. However, the number of publications since 1999, the year of the first study on this topic, shows a growing trend, especially since 2013, i.e. since legislation has given model risk an independent status compared to operational risk.

With our literature review on model risk, we wanted to show that academia needs to pay more attention to the topic, based on what has been highlighted in previous studies.

The bibliometric analysis allowed us to answer the first two research questions (RQ1. What are the most cited documents on the field of model risk? RQ2. What are the most influential journals, authors and countries on this topic?)

The performance analysis revealed that the most influential articles (by number of total citations) are "Enterprise risk management: coping with model risk in a large bank" by Wu & Olson (2010) and “Market risk and model risk for a financial institution writing options” by Green & Figlewski (1999).

The analysis of the sources revealed that the Journal of Banking and Finance is the most influential journal (total citations) on the topic, while the Journal of Risk Model Validation is the most prolific journal (total publication).

The most cited authors on the topic are Wu from the University of Chinese Academy of Sciences, School of Economics and Management, and Olson from the University of Nebraska, Department of Management. The most prolific authors are Jacobs and Tunaru, from the University of Sussex Business School.

Finally, with reference to the most influential countries, we find that the United States represents the most cited and most prolific country on the subject of model risk in the banking sector.

The network analysis revealed that three main areas of research have developed around the concept of model risk (RQ3: What aspects of model risk have been addressed in the literature?)

1) Studies highlighting the impact of model risk on regulatory capital requirements, particularly on the calculation of market risk.

2) Studies highlighting the impact of model risk on credit risk assessment, particularly stress testing and backtesting.

3) Studies that observe the potential applications of new AI and ML technologies to risk management and question banks' ability to manage and monitor these applications.

Regarding timing, as the overlay analysis shows, the studies of the last two years focus on the third thematic area. They discuss the benefits of greater computational capacity and competitive advantage in the face of the risks associated with greater complexity and, consequently higher model risk. Finally, the thematic mapping reveals that the themes of emerging technologies and changes in banking regulations appear to be niche, whose importance in the literature is not yet strongly developed.

7.1 Open questions and challenges for the future

A cross-sectional review of the main issues raised in the literature that need to be effectively addressed and resolved allows us to outline open questions and challenges for the future and consequently answer the fourth research question (RQ4: Which questions are still open and require further research and knowledge?)

The main critical issues related to the topic, representing open questions and future research perspectives, are conceptual, computational, and organizational.

From a conceptual perspective, it is essential to define clearly what a model is and is not. From this perspective, uncertainties arise when identifying the management object (De Jongh et al., 2017). An inventory of models and non-models that are treated differently is essential. In other words, such models (e.g. quantitative processes that produce a specific, deterministic output and not assessments, estimates or forecasts) probably cannot be validated. However, their existence needs to be known and reported to the internal validation function.

Another critical issue to be addressed is the difficulty of controlling the discrimination that innovative techniques, such as ML, produce. Typically, these techniques are used in the value chain of credit risk, insurance risk or other types of financial risk. Models based on ML may be characterized by biases in the training data (outliers and data with incorrect information) or biases in the methodology itself, which can lead to discrimination and reputational problems. The process of validating these models to control for model risk should also check for fairness and the possible presence of bias (Fritz-Morgenthal et al., 2022). The complexity of models, compounded by the application of new computational techniques, also leads to difficulties in understanding, communicating and interpreting the models and results (Hill, 2019).

From a computational perspective, the literature carefully addresses critical issues related to the measurement of model risk in the financial risk domain. At the same time, any measurement system is ineffective if the input data are not of good quality. The problem of data quality is still proving unresolved in the banking sector. This is underlined by the parallel process of data migration to the cloud, which brings regulatory issues and, consequently, data protection risks (e.g. the GDPR) (Gan et al., 2021; Hill, 2019). Another issue is the generalization of learning models of sophisticated systems, which are often dependent on the initial sample and do not perform well when applied to other data; in this context, techniques are used to avoid overfitting. Greater computational complexity is a barrier to the use of models for regulatory purposes, given the approval times required by regulators. However, these models help to increase the efficiency and effectiveness of management processes and decisions, such as lending, pricing and recovery decisions.

Conceptual and computational issues are intertwined with organizational issues. First, there is a need to identify some roles in MRM that are not yet well defined, especially the owners and end users of the models, to delineate responsibilities clearly.

Model risk has not yet acquired the significance of first-level risk. Therefore, its governance is not yet formalized and clear. The model risk owner needs to interact with the end user to identify and address any model malfunctions (Haakman et al., 2021). On the other hand, model users are the first line of defence in relation to model risk, as they are the first to notice when a model is not functioning correctly. Model validation is an important phase, but it requires precise and advanced skills for which new professions are needed. In addition to skills, complete and timely documentation can also support model analysis, control and validation (Haakman et al., 2021; Garro, 2020). In this respect, new technologies, such as technical writers, can be valuable allies.

The outstanding issues that need to be addressed are far from trivial. However, good MRM could lead to significant savings in the direct costs of fixing model errors (man hours, consultancy, etc.) and in the indirect costs arising from any add-on capital imposed by the ECB.

7.2 Research agenda

The analysis revealed several issues that research could explore to improve knowledge about model risk (Table 5).

Table 5: Research agenda

Cluster	Theme	Challenges / Future Research Areas	Main references
Cluster 1 (red)	Model risk in regulation	• Model risk hedging strategies • Quantification of model risk for non-financial risks (e.g. climate risk) • Development of adequate risk measures and capital requirements that take model risk into account • The impact of model risk on capital requirements based on the most commonly used risk measures • The impact of model risk on different risk classes and liquidity horizons	Kerkhof et al. (2010); Alexander & Sarabia (2012); Kellner & Rosh (2016); Barrieu & Ravanelli (2015); Farkas et al. (2020)
Cluster 2 (blue)	Model risk and credit risk	• Evaluating the model risk of internal models for estimating PD and LGD using European samples and data relating to the last five years • Studying adjustments for model risk reduction in the context of stress tests to overcome the instability of the relationships between macroeconomic variables and risks	Wu & Olson (2010); Berg & Koziol (2017);

Cluster 3 (green)	Model risk and new technologies	• Building a framework based on best practices and existing literature on the governance of all phases of the model's life Implementing a clear definition of roles and responsibilities in the model risk management framework throughout the model lifecycle • Addressing the challenges that exist in controlling and validating particularly new models or models with a large number of variables • Studying the governance of models based on ML and AI within credit institutions and companies belonging to different sectors • Studying, through case studies, the application of new technologies in the model validation phases • Learning more about the compliance of ML models with regulations • Developing guidelines for exploratory data analysis and data integration techniques, documentation, model governance, monitoring and control • Combining the use of AI-based models with ethics issues	Haakman et al. (2021); Hill (2019); Jacobs (2018); Gan et al. (2021); De Jongh et al. (2017); Garro (2020)

7.2.1 Model risk in regulation

In regulation and compliance, new research frontiers are opening up strategies to mitigate model risk and techniques to quantify model risk in the area of nonfinancial risk. Climate factors and their direct or indirect impact on credit institutions are a topical issue to which banks must respond through estimations, climatic stress tests and counterparty and risk sector assessments. All of this increases the risk of valuation errors and thus the model risk. Therefore, it is necessary to explore appropriate risk measurement techniques and capital requirements that consider the models' uncertainty. Moreover, given the purely long-term impact of some extra-financial factors, such as climatic factors, it might be interesting to assess the impact of model risk not only for different risk classes, but also for different time horizons.

7.2.2 Model risk and credit risk

In the context of the relationship between model risk and credit risk, the model risk of the internal models used to estimate PD and LGD could be assessed by considering new macroeconomic scenarios. Events that have no equivalent, such as the COVID-19 pandemic and the energy crisis, now render the scenarios created and used by banks obsolete, increase uncertainty in the estimation of impacts, and cause estimates of PD and LGD to be biased and inconsistent between banks but also within the same bank over time.

7.2.3 Model risk and new technologies

Future research could establish a framework for managing all stages of the model life cycle to help firms implement compliant and effective MRM and overcome the organizational criticisms that are a source of model risk, such as the division of responsibilities between owners and model users.

Future studies could explore the role of new technologies in model risk. Conducting case studies could make it possible to examine the management of models based on ML and AI in both credit institutions and companies in different sectors using a practical approach. It could also examine how banks use ML and deep learning to investigate areas such as financial and cybercrime. The same logic could be used to examine how new technologies can facilitate the model validation phase.

An extensive debate is also underway on the potential ethical and reputational risks of complex models based on the technologies mentioned above, whose use in the credit value chain may lead to biases resulting from data learning. Principles, requirements and control tests of the model should also consider the very purpose of the model. Possible solutions to this problem, which are difficult to identify, present a challenging prospect for investigation.

7.2.4 Recent trends and model risk

Finally, future research can intertwine the issues of model risk and emerging technologies with those related to ESG factors. The growing regulatory pressure on these issues leads credit institutions to develop new methods for assessing counterparties based on environmental, social and governance performance. Supervisors require banks to integrate ESG risk assessments into their risk management functions. In this context, one of the most critical problems is related to data availability and evaluation metrics. Future research could further investigate the inherent risks of CCR assessment models by considering their environmental riskiness. In particular, a known problem is linked to the discrepancies between the ESG ratings that institutions acquire from various external providers (Berg et al., 2022). Future research could explore how the same counterparty's credit risk changes using ESG ratings from different providers.

Similarly, models are being developed for integrating ESG factors into investment processes, which could create distortive effects, rewarding greener but at the same time less financially stable companies. For institutions, these distorting effects represent, a new source of model risk to be explored.

8 Concluding remarks

Through a bibliometric analysis, this work has made it possible to provide a representation of the available knowledge on the topic of model risk, offering future scholars possible areas of investigation that could address borderline issues, unresolved questions or those that go beyond the limits of the present study.

Although in the literature the use of Scopus as the only reference database is a consolidated practice, supported by numerous evidence (Goodell et al., 2021; Pattnaik et al., 2020; Archambault et al., 2009), the bibliographic data from additional databases (e.g. EBSCO, WoS, Google Scholar) could guarantee other interesting insights and a larger sample of studies. Furthermore, our study focuses on the study of model risk from the point of view of financial institutions. It might be interesting to manipulate the search string to find studies that analyze model risk in other contexts (e.g. Chalkiadakis et al., 2021).

The bibliometric analysis carried out allowed us to identify the main areas of interest in the literature around the concept of model risk in the banking sector and to understand that the literature on model risk is still young and small and has only developed significantly after the publication of the European Directive CRD IV, which defined model risk for the first time.

Over the years, the challenges for MRM are likely to increase exponentially because more and more models are being used in all functions and decisions, new technologies are ubiquitous and turbulent economic scenarios lead to the adaptation of the models used. . In the background, the focal theme of sustainable finance is added to these factors and the latter opens new paths to new technologies, AI, ML and big data. Although the current application of new technologies in research on sustainable finance is almost practically nonexistent, it is expected that in the coming years AI and ML techniques can be implemented to select credit applicants on the basis of sustainability criteria. Big data can be used to gain insights into public sentiments about sustainability issues and emerging blockchain technology can be used to track and flag impact concerns or successes in the activities of sustainable financing on sustainability goals (Kumar et al., 2022).

Also, the rapid change in economic conditions requires models to adapt to the external environment, which brings with it the possibility of losses due to model risk. Banks need to continuously monitor their models to respond to changing model conditions, mitigate the resulting risks and meet regulatory requirements for model validation (Argyropoulos & Panopoulou, 2019). To address these challenges, institutions in different regions take different approaches. In Asian countries, especially China, banks are already recalibrating or revising their models. In North America and Europe, model correction takes the form of cautious overlaps (e.g. through expert judgement), while the search for more systematic approaches is progressing rapidly. AI and ML are tools that can help with model validation in particular, to assess its conceptual soundness, analyze data quality and make basic corrections, all in a continuous and automated way. On the other hand, this means adding more models of high complexity, which is another challenge that the risk management model must face (Ali & Daly, 2010). Addressing these challenges in MRM will certainly require creativity, resourcefulness and support from senior management, as well as additional staff with a variety of quantitative and qualitative skills.

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