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Review Article

A Bibliometric Analysis on Agent-Based Models in Finance: Identification of Community Clusters and Future Research Trends

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Agent-based models are computational approaches used to reproduce the interactions between economic agents. These models are widely applied in many contexts to get deeper understanding about agents' behaviors within complex systems. In this paper, we provide a bibliometric analysis about agent-based models in finance and, considering bibliographic coupling, we identify the presence of two distinct clusters of research communities, i.e., financial economics and econophysics. Cluster-specific thematic analyses are conducted to understand if the two communities are characterized by different emerging and motor topics. By highlighting several differences in the clusters, we also show the two research communities specialized in different specific topics.

1. Introduction

Since the beginning of the 1990s, agent-based models have been an emerging topic in economics literature. In finance, agent-based models have been used to reproduce the well-known stylized facts of financial markets, such as heavy tails, volatility clustering, and long memory (see Cont [1]). Economic models usually have a representative agent who is perfectly rational and uses the principle of utility maximization to act. In contrast, agent-based models, which originated in statistical physics, allow us to go far beyond the assumptions of classical economics.

Despite the presence of some review articles on the topic (e.g., see Chakraborti et al. [2], Chen et al. [3], Huang [4]), we note that these studies have been conducted with the adoption of qualitative approaches. In contrast to classical qualitative reviews, modern and more appropriate quantitative techniques exist and can be successfully used to conduct a systematic literature analysis.

In this sense, bibliometric studies provide systematic, transparent, and reproducible reviews conducted through statistical measurement of science (Aria and Cuccurullo [5]). The aim is to deeper understand the authors' network structures, i.e., the analysis of scholars' communities, and to identify trending and declining topics (e.g., see Aria et al. [6]) as well as the determination of journal performances. Despite a few recent attempts (e.g., Paltrinieri et al. [7] and Khan et al. [8]), the use of *science mapping* approaches for literature review in finance is still poorly explored.

Considering the qualitative analyses on the topic, it emerges that the most important contributions have been published in econophysics and economics journals. Therefore, it is natural to suppose that two clusters of research communities exist when studying the literature on agent-based finance models. If two research communities exist, it is interesting to study if they are specialized in specific topics and which these topics are. To the best of our knowledge, this aspect has never been investigated by previous studies concerning agent-based modeling in finance.

Therefore, the paper aims to contribute to previous literature in two ways. First, by using the R package bibliometric developed by Aria and Cuccurullo [5], we aim to fill the gap related to quantitative literature reviews by providing the first bibliometric analysis for agent-based models in finance. Hence, the paper aims to identify emerging and decreasing topics in financial agent-based modeling. Second, we explore the differences in the topics among distinct research communities through cluster-based thematic maps, identified by performing a coupling analysis (Kessler [9]).

Our main findings show the presence of two main clusters of scholars' communities that are identified based on the journals in which the papers are published. As the main result, we demonstrate that the econophysics research community, represented by the articles published in physical sciences journals, clearly differentiates from the economics and finance community, represented by the articles published in finance-related journals. In particular, asset pricing and trading give motor topics for the econophysics community. In contrast, those of the economics community are related to financial crises and the interaction of finance with macroeconomic fluctuations. Furthermore, our results highlight that the study of market microstructure is an emerging topic for the econophysics community, while asset pricing is becoming more popular for economics. These findings can serve as a tool to orientate researchers in identifying the most suitable journal—more precisely, its area, i.e., either econophysics or financial economics—for their last research on the topic.

The paper is structured as follows. Section 2 provides a brief overview of the most relevant papers in financial agent-based modeling, while Section 3 discusses the collected data and main descriptive results obtained with quantitative techniques. A detailed analysis of the most influential sources is provided as well. Section 4 demonstrates the presence of clusters of journals with a coupling algorithm. Then, Section 5 provides a detailed within cluster analysis, showing cluster-specific thematic maps as well as the analysis of trend topics. In the end, a discussion of the results and concluding remarks are presented.

2. Brief Overview about Agent-Based Modeling in Finance

The works have been extended in three representative areas:

(i) Multiagent models for modeling orders
(ii) Agent-based modeling for wealth distributions: Kinetic theory models
(iii) Agent-based modeling based on game theory

In economics, agent-based models are considered a competitor of standard dynamic stochastic general equilibrium (DSGE). Fagiolo and Roventini [10] present an engaging survey about the contribution of agent-based models in economics.

According to Fagiolo et al. [11], in finance, the agent-based models allow for more descriptive richness, as they describe ecologies of agents, locally interacting through nonobvious network structures, learning to use incomplete information, and competing within imperfect markets.

Until the beginning of this century, the agent models incorporated from behavioral finance were built with agents that can exchange actions according to exogenously defined utility functions that reflect their preferences and risk aversion. Although they have achieved some of their goals, they suffer from many drawbacks: first, they are very complex, and it can be a challenging task to identify the roles of their many parameters and the types of dependencies between them; second, the chosen utility functions do not necessarily reflect what is observed in the mechanisms of a financial market.

The first work simulating a financial market is carried out by Stigler [12], where the author studies the effect of the SEC regulations on the American market using empirical data from 1920 to 1950. In 2008, Slanina [13] implements the model developed by Stigler and discovers that it can reproduce the behavior of heavy tails, although with an α far from the empirical one, as expected due to the restrictions of the original model.

Garman [14] makes an early study of a double auction market with a point of view that does not ignore the time structure and also defines the order flows. The main contribution of this work is to provide for the first time an empirical study of the market microstructure. In both models, orders arrive at the market randomly within price ranges. The agents do not observe the market; therefore, their strategy does not depend on it, so these models are considered *zero-intelligence* models. However, this concept is attributed to Gode and Sunder [15] to explain the blind behavior of operators who randomly send orders to the market.

These authors study two types of market operators: with restrictions and without them. The authors' goal was to show that double auction markets exhibit intrinsic allocation efficiency (the ratio of the total profit earned by traders divided by the maximum possible profit) even with zero-intelligence traders. An interesting fact is that the price series resulting from the actions of zero-intelligence traders are much more volatile than those obtained from constrained traders. Cont and Bouchaud [16] introduce noise traders that follow herd behavior. The idea is also used by Raberto et al. [17]. Lux and Marchesi [18] propose an agent model in which traders interact with each other. In all these models, the price variation depends on the balance between the buy and sell orders throughout the development of the model.

An important step is when the models consider the limit orders that are sent to the market but are not executed. Chiarella and Lori [19] build an agent model in which the operators send the orders to the market according to the types established by Lux and Marchesi [18], that is, chartists, fundamentalists, and "noise" traders. Orders are stored in an order book.

However, the most important step is taken when the rational agents that make up the models in economics tend to disappear and be replaced by the notion of flows: the orders are no longer sent by an agent that follows a strategic behavior, but are seen as an arriving flow, whose properties must be determined by empirical observations of market mechanisms. Therefore, order modeling requires more stylized facts. Market orders, limit orders, arrival time, and execution are studied. Bouchaud et al. [20] and Potters and Bouchaud [21] provide the statistical characteristics of the order book itself and are the basis for zero-intelligence models, in which stylized facts are expected to be reproduced by the properties of the order flows and their structure. Chalet and Stinchcombe [22] propose an order flow model where limit orders are stored in a mechanism that removes them if not executed.

Since the 1990s, physicists have made fascinating contributions to this research line. Bak et al. [23] developed the first physics-inspired model. The author considers a market with N noise traders capable of exchanging one stock at a time. As the author points out, the simulation process is based on a physical reaction-diffusion model of the type.

In the model, no broad tails are observed in the returns, but the typical decay of the distribution's tails seems to be visible. The main drawback of the model is that moving orders are unrealistic for modeling an order book. Since it does not reproduce any known financial exchange mechanism, it cannot be the basis of a more general model. However, the scientific community seems to agree that the basic model is fascinating due to its simplicity. Maslov [24] maintains the structure of Bak et al. [23], but introduces some more realistic assumptions of market evolution. First, the limit orders are submitted and stored in the model, without moving. Second, limit orders are posted around the best quotes. Third, market orders are submitted to trigger trades. Numerical simulations show that this model exhibits non-Gaussian heavy-tailed distributions of returns. However, the Hurst exponent of the price series is still $H = 0.25$ in this model. This model introduces interesting innovations in order book simulation: an order book with limit (fixed) orders, market orders, and the need to cancel orders, waiting too long in the order book. These features are of paramount importance in any following order book model.

Subsequently, Chalet and Stinchcombe [22] continued the work of Bak et al. [23] and Maslov [24] and developed the analogy between the dynamics of an order book and an infinite one-dimensional grid, where the particles of two types (ask and bid) are subject to three types of events: deposition (limit orders), annihilation (market orders), and evaporation (cancelation). It appears that the series of price returns simulated with this model exhibits a Hurst exponent of 0.25 for short time scales, and that it tends to $H = 0.5$ for longer time scales.

These three models can successively isolate the essential mechanisms to be used when simulating a realistic market: order is the smallest unit; sending order is the time dimension; the presentation of market orders and the cancelation of orders are taken into account. On the one hand, one can try to describe these mechanisms using a reduced number of parameters, using a Poisson process with constant rates for order flows and constant volumes. On the other hand, one can try to fit more complex empirical distributions to market data without analytical concerns. Mike and Farmer [25] develop a model that proposes a more advanced calibration with market data when placing and canceling orders. With regard to volume and time of arrival and execution, the assumptions of the previous models are maintained, with no distinction being made between market orders and limit orders.

The results of this empirical model are quite satisfactory concerning the yield and spread distribution. As for the drawbacks, we can mention the instability of the order book. Simulations using empirical data show that situations can occur that empty the order book due to extreme market events. Another drawback is that the model does not take volatility clusters into account. In this line, Gu and Zhou [26] propose some model variations. Another major drawback of the model is how the order signs are simulated. As the authors pointed out, using an exogenous fractional Brownian motion leads to correlated price returns, which contradicts the stylized empirical facts.

In all the models discussed above, the order flows as independent processes. Under certain modeling constraints, the order books can be viewed as a Markov chain. In any case, even if the process is empirically detailed and nontrivial, they work with the assumption that the orders are independent and identically distributed. This very restrictive (and false) hypothesis is similar to the representative agent hypothesis in economics: commands that are sent successively and independently, and we can expect nothing more than regular behavior. Following the work of economists like Kirman [27–30], it is necessary to translate the heterogeneous property of markets into agent-based models. Agents are not identical or independent.

The model presented by Cont and Bouchaud [16] considers a market with N agents trading stock with a price. The idea is to model the diffusion of information between agents by randomly linking their demand through groups. Therefore, this simple model exhibits thick tails in the distribution of returns, with decay reasonably similar to that of the empirical data. Therefore, the authors show that taking into account a naive communication mechanism between agents (herd behavior) can move the model away from Gaussian convergence and produce nontrivial forms of return distributions.

Lux and Marchesi [18] proposed a model very much in line with agent-based models in behavioral finance, but where business rules are kept simple enough that they can be identified with more realistic agents' behavior. This model considers a market with N agents that can be part of two different groups of traders: one group of traders are "fundamentalists," who share an exogenous idea of the value of the current price, and other traders are "chartists" (or trend followers), who make assumptions about the price evolution based on the observed trend (moving average). However, the number of parameters involved and the complicated transition rules between agents make the clear identification of the sources of the phenomena and the calibration to market data complex and intractable.

3. Data Collection and Research Questions

We collect the database on the basis of a query to the Web of Science (WoS) website on January 7, 2022. The WoS database is used in many bibliometric analysis because of its large coverage of sources: more than 20000 journals, conference proceedings, books, and review articles.

We searched for all the documents related to the topic agent-based model, by using the following query: "Agent-based model*" AND "Finance" OR "Financial market*" OR "Stock market*." The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) scheme (Liberati et al. [31]) was used for the selection process. We considered only papers written in English, and we limited our study only to articles and reviews published between 1992 and 2021, obtaining 1302 entries.

All the analyses shown in this paper have been performed with the open-source R package bibliometric (Aria and Cuccurullo [5]). Table 1 shows the main statistics of the entire collection.

The average number of published papers is about 42 per year. The number of publication shows a positive trend, characterized by an annual growth rate equal to 17.78% (Figure 1).

Figure 1 shows that the scientific interest in agent-based modeling raised especially after the financial crisis. Indeed, as stated by Farmer and Foley [32], the financial crisis highlighted all the weaknesses of DSGE models, based on too strict and unrealistic assumptions. Hence, by using these kinds of models, policy-makers can simulate artificial economies according to alternative scenarios to quantitatively explore the potential effects of each policy.

Most of the articles are published in collaboration. Indeed, single-authored documents are 254 out 1302, i.e., almost the 20% of the total production (see Table 1). In particular, we have that each article has 2 authors on average. Because of the complex nature of interactions that take place among authors over a period of time, the precise nature and magnitude of collaboration cannot be easily determined from standard metrics. To overcome this problem, bibliometric literature proposes the construction of the so-called collaboration index (e.g., see Ajiferuke et al. [33]), given by the ratio between the total number of authors of multi-authored documents and the total number of multiauthored documents. In the selected sample period, we observe a value of the index equal to 2.26, thus confirming the idea that on average there are two authors per document.

Looking at the sources publishing articles about agent-based modeling in finance, we find that Physica A is the most relevant journal with 90 articles published, followed by the Journal of Economic Dynamics & Control with 60 papers published on the topic. Among the 20 most productive sources, we found both journals specifically related to economics and finance, physical sciences, but also journals which audience are both physicists and economists such as PLOS One (with 22 published articles) and Quantitative Finance (with 39 documents). In terms of sources' impact, a citation analysis confirms that Physica A is the most influential source.

Given the above descriptive statistics, the aim of our paper can be summarized by testing the following two hypotheses:

(i) H1: The scientific production is characterized by two (or more) distinct clusters identifying specific research communities.

(ii) H2: The two (or more) distinct research communities specialized in different topics.

Table 1: Main statistics about the collection.

Main information	
Timespan	1992 : 2021
Sources (journals and books)	511
Documents	1302
Average years from publication	7.66
Average citations per documents	14.29
Average citations per year per doc	1.445
References	39299
Document distribution	
Article	1272
Review	30
Authors statistics	
Authors	2587
Author appearances	3498
Authors of single-authored documents	218
Authors of multiauthored documents	2369
Authors' collaboration	
Single-authored documents	254
Documents per author	0.503
Authors per document	1.99
Co-authors per documents	2.69
Collaboration index	2.26

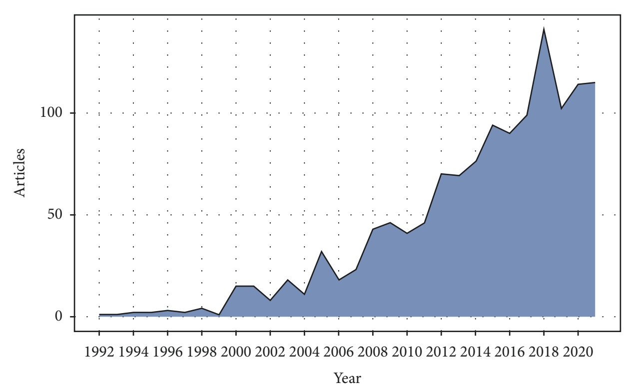

Figure 1: Annual production of articles about agent-based modeling.

The first hypothesis answers the following research question: is the scientific production of agent-based modeling in finance characterized by two or more distinct groups of research communities? If the hypothesis is accepted, it is natural to study the characteristics of such research communities in terms of the analyzed topics. Indeed, we have the second hypothesis to test, which answers the following question: in which topics are the different research communities specialized? This second question is relevant from a scientometric point of view because it can be that a very relevant topic for a given research community can be less critical for another one. For example, using the coupling technique in the context of financial bibliometric analysis, Khan et al. [8] documented the existence of four clusters specialized in different topics such as green finance, financial literacy, and big data. As another example, it is known that, in the context of financial time series clustering, the econophysics community specializes in different topics compared to computer scientists and statisticians (e.g., see Mattera et al. [34]). There are many other examples of such distinctions. In this paper, we try to get deeper insights into the differences between the motor and declining topics in the different research communities through thematic maps.

4. Main Results

4.1. Identification of Research Communities with Coupling. In order to understand if two research communities really exist, we perform a bibliographic coupling analysis on journals (Kessler [9]). The idea behind bibliographic coupling analysis is that if two articles have similar bibliography probably the two works treat a related topic.

In a classical bibliographic coupling analysis, the unit of analysis is papers and their relatedness is determined based on the number of references they share. The number of references in common is normalized by considering the total number of papers cited by the two given documents. Obviously, the strength of the relationship of two documents is higher than more citations to other documents they share. The same logic can be extended to journals by aggregating the reference lists of their respective published papers, and the coupling strength of two journals (or more precisely, of the papers published on these journals) is defined as the size of the intersection of their cumulative reference lists.

Through coupling analysis, we identify 3 clusters of journals, the 33% of the total of sources in our collection. We do not couple sources that publish only one article on agent-based modeling. The distribution of the sources within clusters is shown in Table 2.

Table 2 clearly shows that the first cluster includes quantitative journals with a specific focus on mathematical and physical sciences. For example, it includes journals like Physica A, European Physical Journal B, Journal of Statistical Mechanics, Physical Review E, and others. These kinds of journals welcome contributions from physicists and econophysicists. The only (most relevant) interdisciplinary journals within this cluster are PLOS One and Quantitative Finance.

On the other side, the second cluster contains the majority of economics and financial journals. For example, cluster 2 includes the Journal of Economic Dynamic & Control, Computational Economics, Macroeconomic Dynamic, Economic Modelling, and much others.

Then, the third cluster includes journals of different types. Examples of sources are Expert Systems with Application and Information Sciences that have a specific focus on machine learning and statistics, and Sustainability and Energy Policy that are journals more related to energy and environmental sciences. Nevertheless, the third cluster also includes some economics-related journals, like Applied Economics and Review of Financial Studies, that published few contributions on agent-based modeling.

In general, the third group contains journals that published a lower amount of articles related to agent-based modeling. For example, the most productive journal on the topic is the JASSS with 22 articles, while in the first cluster there is Physica A with 90 papers and in the second one the Journal of Economic Dynamic & Control with 60 contributions. For this reason, we call the sources in the third cluster as residual group.

For each cluster of journals, we filtered the related papers obtaining 3 subcollections. Table 3 shows the main statistics of each subcollection.

Table 2: Most relevant journals within clusters.

Panel A: cluster 1—econophysics	
Sources	Articles
Physica A	90
Quantitative finance	39
PLOS One	22
Complexity	14
European Physical Journal B	13
Entropy	9
International Journal of Modern Physics C	9
Journal of Statistical Mechanics	9
IEEE Access	8
Physical Review E	8
Chaos	7
New Journal of Physics	7
Nonlinear Dynamics	7
International Journal of Theoretical and Applied Finance	6
Chaos, Solitions and Fractals	4
Panel B: cluster 2—financial economics	
Sources	Articles
Journal of Economic Dynamic and Control	60
Journal of Economic Interaction and Coordination	43
Computational Economics	33
Journal of Economic Behavior Organization	32
Economics	15
Advances in Complex Systems	13
Macroeconomic Dynamics	13
Economic Modelling	11
Journal of Evolutionary Economics	11
International Review of Financial Analysis	9
Discrete Dynamic in Nature and Society	8
Intelligent Systems in Accounting Finance Management	8
Economic Theory	7
Finance Research Letters	5
Panel C: cluster 3—residual	
Sources	Articles
JASS	22
Expert Systems with Applications	13
Sustainability	11
Energies	7
Evolutionary and Institutional Economics Review	7
Applied Economics	6
European Journal of Operational Research	6
International Journal of Information Technology Decision Making	5
Journal of Economic Theory	5
Review of Financial Studies	5
Energy Policy	4
Information Sciences	4
Journal of Monetary Economics	4
Mathematical Finance	4
Technological Forecasting and Social Change	4

Table 3: Main statistics about the subcollections.

Main information	Cluster 1	Cluster 2	Cluster 3
Timespan	2000 : 2021	1992 : 2021	1994 : 2021
Sources (journals and books)	47	62	64
Documents	341	402	217
Average years from publication	7.65	7.14	8.14
Average citations per documents	13.2	12.53	16.24
Average citations per year per doc	1.264	1.375	1.627
References	9430	11614	9213
Document distribution			
Article	330	397	214
Review	11	5	3
Authors' statistics			
Authors	687	687	574
Author appearances	956	996	617
Authors of single-authored documents	51	78	34
Authors of multiauthored documents	636	609	540
Authors' collaboration			
Single-authored documents	55	90	35
Documents per author	0.496	0.585	0.378
Authors per document	2.01	1.71	2.65
Co-authors per documents	2.8	2.48	2.84
Collaboration index	2.22	1.95	2.97

According to Table 3, the cluster with the longest timespan is the second one, i.e., the group containing the papers published by the financial economics community. It also contains the highest amount of documents, but lower documents over time ratio than the other two clusters.

Despite the lower timespan of the scientific production, the second cluster, i.e., the one including papers published by the econophysics community, is the one with the highest number of review articles on the topic.

In terms of authors' statistics, from Table 3 we note that clusters 1 and 2 have exactly the same number of authors. However, the financial economics cluster shows a higher amount of single-authored manuscripts. This evidence is also confirmed by the collaboration index that is equal to 1.95 versus the 2.22 of the econophysics cluster. The number of authors per document is also higher in the first cluster than the second.

The time series of the annual scientific production for each cluster is shown in Figure 2.

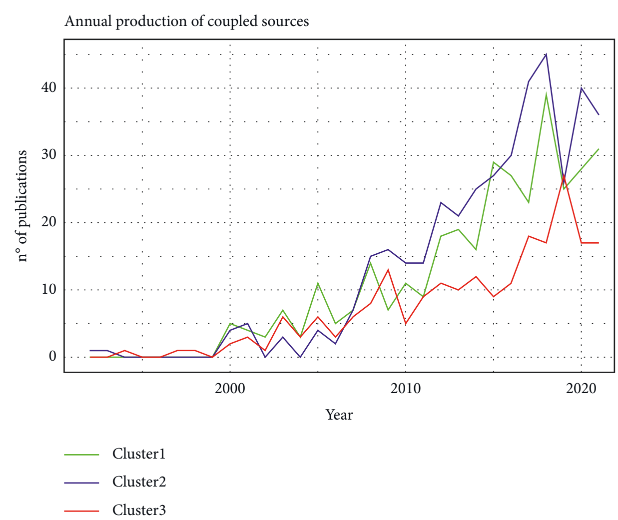

Figure 2: Annual production time series—all clusters.

Interestingly, Figure 2 highlights that the econophysics community represented by the green line in the plot provided a higher production than the other two clusters between 2000 and 2007. Then, after the financial crisis the financial economics community rapidly increased the production of articles about agent-based modeling. This can be explained by the awareness about weaknesses of DSGE models, not able to properly model the complexity of financial markets with its agents.

Figure 2 confirms the evidence that the third cluster characterizes a less productive community. Indeed, the red line in the plot is always under the red and green ones. This is true especially after the financial crisis.

As recent evolution, we note a renewed interest in the econophysics community about agent-based modeling, since the green line has a positive inclination. Conversely, the blue line is showing a decreasing behavior, suggesting that the financial economics community is reducing its production about this topic in recent years.

The analyses conducted so far clearly suggest the presence of three groups of communities, identified on the basis of journals. In what follows, we provide a deeper investigation about the themes that characterize each group.

4.2. Identifying Cluster-Specific Emerging and Motor Topics with Thematic Maps. To compare the research fronts of the 3 communities, highlighting similarity ad differences, we perform a thematic analysis (Cobo et al. [35]) on each subcollection of papers. Thematic analysis is based on

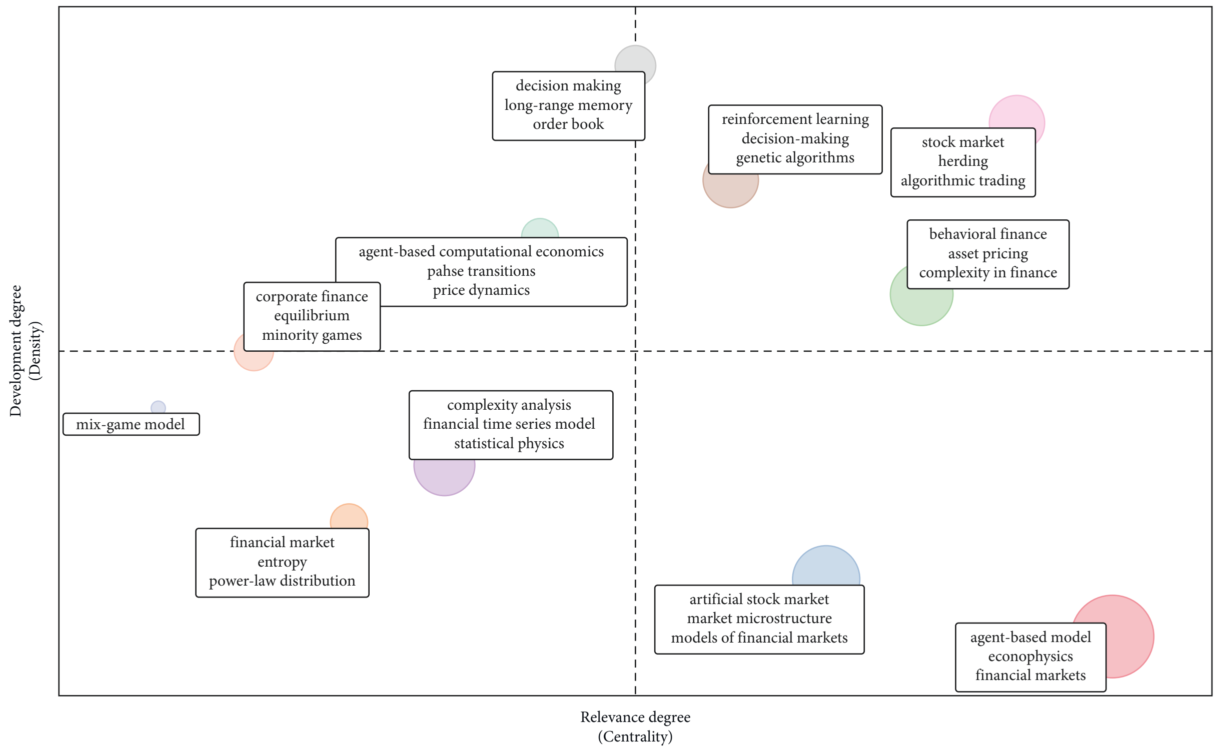

Figure 3: Thematic map—cluster 1.

network analysis tools. The starting point is to assume that each research field or topic can be represented as a set of strictly linked terms (e.g., keywords, terms extracted from titles and abstracts). In this paper, we consider author's keywords to represent the core of each publication. The relationship between couple of terms is measured by their co-occurrences (i.e., the number of times two terms appear together in a paper). We normalize the co-occurrences among terms with the association strength, as proposed by van Eck and Waltman [36]. The association strength is a normalized measure, where a 0 value means that the two terms never co-occur and a 1 value means that the terms co-occur in all papers. The association matrix among terms can be represented as an undirected weighted graph. By performing a community detection procedure on this graph, it is possible to identify subset of strictly related terms, reflecting the different topics embodied in the collection. The themes identified by the community detection are summarized on a thematic diagram (Callon et al. [37]), according to *Callon centrality* (x-axis) and *Callon density* (y-axis). Centrality can be interpreted as the relevance of the topic in the entire research domain, while density reflects its development. Having in mind this, it is possible to define four typologies of topics:

(i) Topics in the upper-right quadrant are the motor themes. They are characterized by both high centrality and density. This means that they are well developed and relevant for the domain.

(ii) Topics in the lower-right-hand quadrant are basic and transversal topics. They are characterized by high centrality and low density. These themes are relevant for a research field and pertain to general topics transversal to its different research areas.

(iii) Topics in the lower-left quadrant are both weakly developed and marginal. They have low density and low centrality, mainly representing either emerging or disappearing topics.

(iv) Topics in the upper-left-hand quadrant are the highly developed and isolated, named as niche themes. They have well-developed internal links (high density) but unimportant external links and thus are of only limited relevance for the field (low centrality).

Each topic is labeled with the its most occurring keywords, assuming that it is representative of the topic itself. The size of topic is proportional with the total occurrences of the keywords that it includes.

As previously highlighted, the first cluster contains the journals devoted to econophysicists. Figure 3 shows the thematic map for the econophysics cluster.

The keyword econophysics occurs very frequently for articles included in this group, suggesting that the assigned label is correct. Emerging cluster's topics are the simulation of artificial stock markets for the analysis of market microstructure, microstructure noise, and the behavior of traders. Then, motor topics can be identified in behavioral finance-related, e.g., herding, with application to asset pricing and trading. In other words, it seems that the interest of econophysics community is mainly devoted to more individual-oriented aspects of finance. As briefly discussed

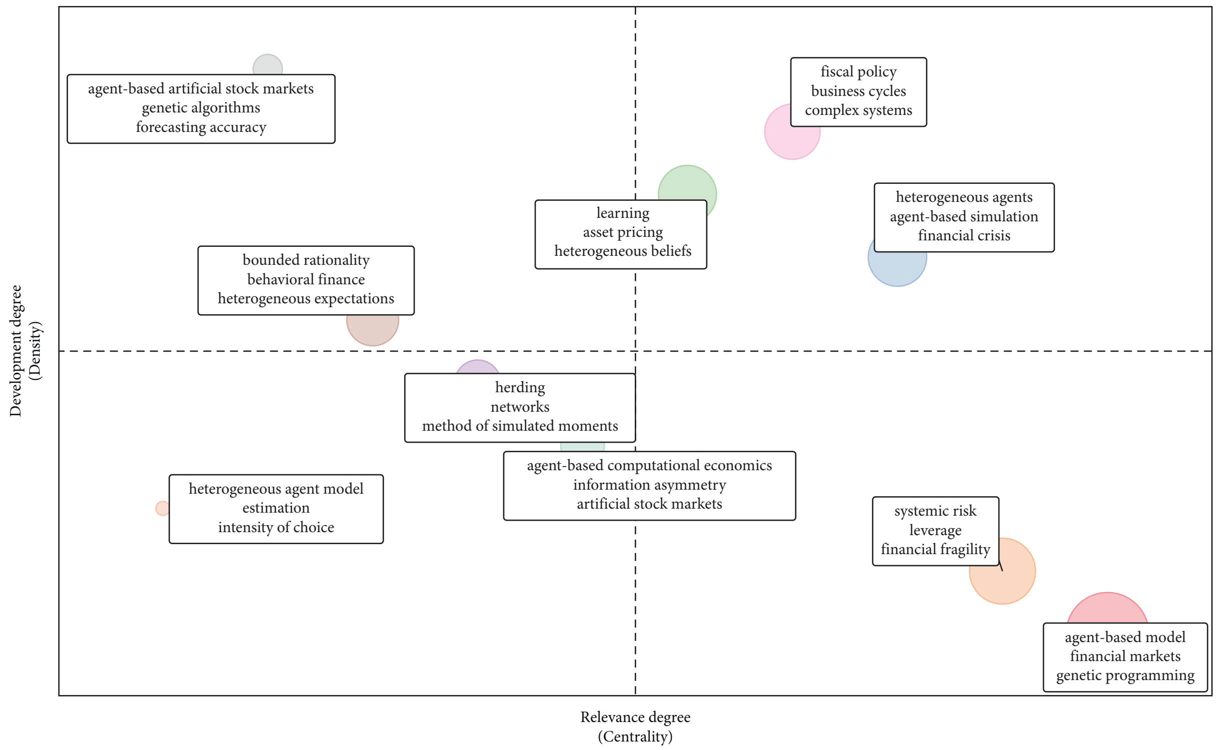

Figure 4: Thematic map—cluster 2.

in Section 2, a relevant topic for econophysics is still represented by behavioral finance. Behavioral finance aims at improving financial modeling based on the psychology of the investors. In the context of agent-based modeling, it seems that the econophysics community is more specialized in building models in which agents make investment decisions according to utility functions reflecting their psychology. Although this topic is a tradition in econophysics, it still represents a motor topic deserving increasing research efforts.

Niche topics are represented by corporate finance application of the agent-based modeling. Conversely, long-range dependence seems to be a niche topic that is becoming very popular. In particular, the interaction between decision making under long-range dependence and market microstructure noise is of interest. Indeed, such topics are in the middle between the plot quadrant identifying niche and motor topics. However, the analysis of power-law distributions and entropy seems to be a declining topic that has gotten more attention in the past years. Another declining topic is the statistical modeling of financial time series, which has become more important for econometricians and statisticians than for academics in econophysics.

The second cluster includes the journals devoted to financial economics community. Figure 4 shows the thematic map for this cluster.

In the financial economics community, the analysis of themes related to economics, such as fiscal policy and business cycle analysis, represents motor ones. Similarly, also the use of agent-based modeling to study the effect of financial crisis and the interaction between finance and macroeconomic shocks are motor topics. Then, the analysis of systemic risks and financial fragility of markets are basic and central topics not very dense but relevant for this cluster. The use of agent-based models employing learning and asset pricing seems to be an important emerging topic for this group. The learning approach plays a central role in modern macroeconomics, and this is confirmed by Figure 4. In models with learning, the economic agents form their expectations by estimating and updating forecasting models in real time (see, e.g., [38]). Therefore, we find that the use of learning in asset pricing problems is expanding topic and deserves future research efforts.

Studies devoted on bounded rationality and, more in general, behavioral finance based on heterogeneous expectations can be identified as niche topics as well for this cluster. Similarly, herding behavior and network structures in financial markets seem to be marginal topics. This is a significant difference with respect to the econophysics cluster (Figure 3), for which behavioral finance is a very important topic. This evidence highlights a clear difference between the two communities: while econophysics is more oriented on studying the complexity arising because of, among the others, investors' psychology and beliefs, the economics community is more focused on the interaction between macroeconomics and finance, thus adopting a more aggregate perspective in the analysis of the problems.

The third cluster identifies a mixing community characterized by a lower production about agent-based modeling. Figure 5 shows the related thematic map.

This cluster includes papers which cannot be clustered with any of the two main research communities, thus

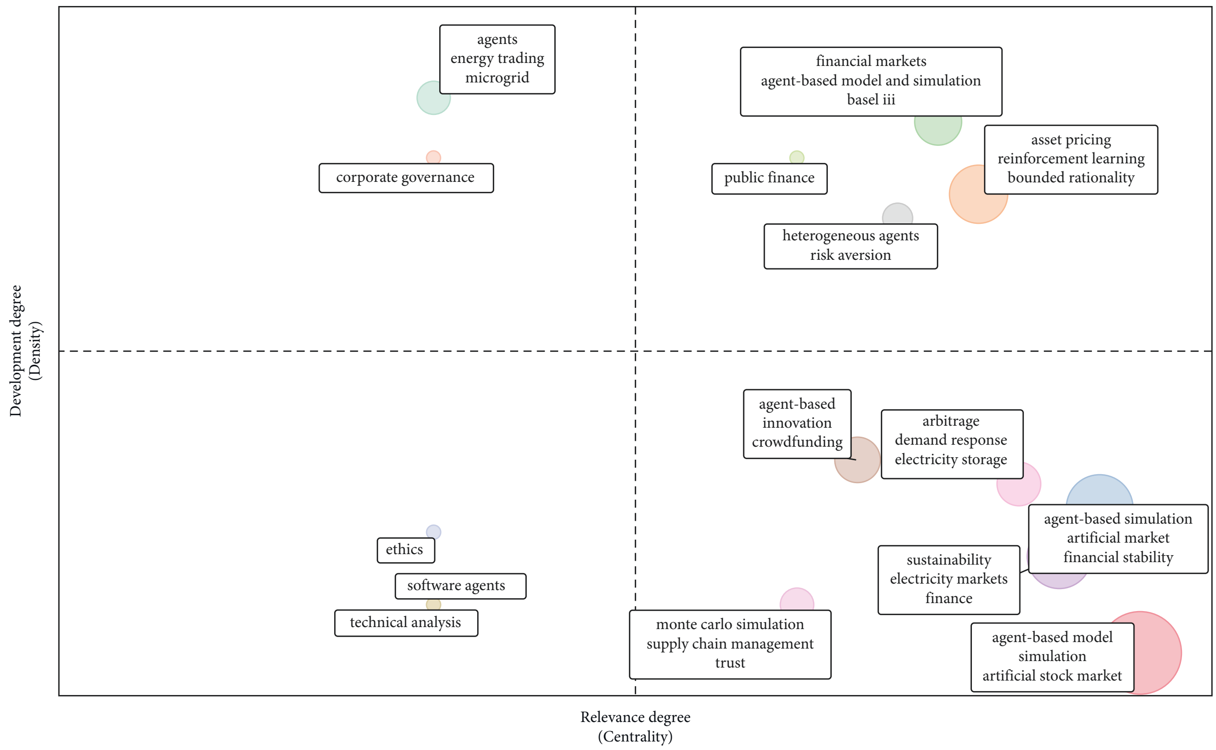

Figure 5: Thematic map—cluster 3.

forming a sort of residual cluster. In fact, from the thematic map in Figure 5, we observe that the basic topics of articles included in this group are of a great variety. Examples are given by sustainability, innovation, and crowdfunding, supply chain as well as more commodities-related topics such as the electricity storage. Overall, it seems that central topic of this third cluster is managerial-related.

On the side of motor topics, Figure 5 identifies the application of reinforcement learning for asset pricing, which is a more individual-specific topic, but also to the analysis of financial stability regulation, such as Basel III, and public finance which are topics studying more problems following an aggregate perspective. The analysis of energy trading and corporate governance are niche topics.

5. Discussion and Final Remarks

As specified in the introduction, agent-based modeling involves using computational models to reproduce interactions between economic agents in complex systems. Agent-based models are considered a competitor of the standard dynamic stochastic general equilibrium (DSGE), based on much more strict assumptions.

The bibliometric analysis conducted so far highlights exciting points of discussion. First, we have seen that the agent-based models became very popular after the 2008 financial crisis. This is evident by looking at the total amount of papers published after 2008.

From the first analysis of relevant sources, we found an interesting distinction between journals devoted to economics and finance and those related to physical sciences. Based on this preliminary evidence, we conducted a coupling analysis on journals to assess if two separate communities publishing about agent-based models in finance exist.

Indeed, it is clear that while financial economists tend to publish in economics-related journals, physicists use to publish in physics journals. By performing the coupling algorithm based on the similarity in papers' references, we found the existence of three separate groups.

Most papers published in physical sciences journals are included in the first group. Therefore, we labeled it as *econophysics* cluster. Then, in the second cluster, most sources are published in financial economics journals. In the third group, instead, we found the presence of journals that do not use to publish articles on agent-based models, i.e., that are less productive. Hence, we labeled this third cluster as *residual*.

The thematic analysis has been conducted with respect to the different clusters. The findings highlight interesting points of discussion.

First, all the clusters contain a general agent-based model topic, identified as a fundamental topic. However, it is important to note that the keyword econophysics is present only for the papers placed in the first cluster, i.e., confirming the presence of a cluster characterized by the econophysics community.

The three clusters differentiate each other in terms of treated topics. In particular, we observe that many topics are present within more than one cluster but with a different degree of relevance. For example, let us consider the case of herding behavior modeling. In the econophysics cluster, it is a motor topic, while for the financial economists' community, it is an emerging topic. In this sense, econophysicist anticipated the financial economists. However, even if this topic is quite traditional in econophysics, it still represents a motor topic deserving increasing research efforts.

Another interesting example is the case learning. In both the communities, it is an important topic. However, in the two communities it takes different forms. In the case of econophysics, learning is intended from the deep learning point of view. Indeed, in the reinforcement learning there is an agent which interacts with an environment through a reward function. In reinforcement learning algorithms the agents take actions with the aim of maximizing such a reward. Differently, in macroeconomic learning the agents form their expectations by updating forecasts in real time. The kind of complexity associated with the two approaches is quite different.

Then, there is a net distinction in the applicative domain of agent-based models between the two communities. Indeed, the econophysics community is more specialized in building models in which agents make investment decisions according to utility functions reflecting their psychology. Although this topic is a tradition in econophysics, it still represents a motor topic deserving increasing research efforts. In other words, while the econophysics community is only interested in treating the case of the stock market, the financial economics literature commonly models the interaction between financial markets and macroeconomic policies. Indeed, papers dealing with keywords like business cycle and fiscal policy that identify a macroeconomic theme are a motor for the second cluster and are absent for papers placed within the first cluster.

Moreover, from thematic maps, we also understand that an important topic treated by the financial economics community is related to financial stability and systemic risk. We did not find these topics in the papers belonging to the econophysics cluster. Vice versa, in the first cluster, we observed a higher relevance to behavioral finance topics. This fact highlights another clear difference between the two communities: while econophysics is more oriented on studying the complexity arising because of, among the others, investors' psychology and beliefs, the economics community is more focused on the interaction between macroeconomics and finance, thus adopting a more aggregate perspective in the analysis of the problems. Studies devoted on bounded rationality and, more in general, behavioral finance are less relevant in the economics cluster than in the econophysics one.

In summary, our bibliometric analysis highlighted the presence of well-separated community groups identified by journals in which the papers are published. This aspect represents a contribution to our paper. Indeed, the difference between this paper and previous studies mainly lies in the distinction between qualitative and quantitative approaches used in the review. Because of the intrinsic difference in the approaches, identifying these clusters with their own motor and emerging topics has never been highlighted.

These findings open up to add comments. First of all, the two communities are specialized in different topics, i.e., behavioral finance and individual-oriented (econophysics) versus macroeconomics and aggregate-oriented (economics). Second, from the above analysis, it seems that the two communities do not collaborate and read each other. This can be problematic in terms of future developments of agent-based modeling, because the two research communities have their expertise, and the research would surely benefit from their intersection.

We think that this contribution can push researchers from both communities to interact more in the near future. Furthermore, due to the differences in the trending topic between the two communities, we also think that findings can guide researchers in identifying the most suitable journal for their last research on the topic.

Data Availability

Data source is Web of Science (WoS). Results of analysis is available under request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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