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MACHINE LEARNING AND TRADITIONAL ECONOMETRIC MODELS: A SYSTEMATIC MAPPING STUDY

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Abstract

Context: Machine Learning (ML) is a disruptive concept that has given rise to and generated interest in different applications in many fields of study. The purpose of Machine Learning is to solve real-life problems by automatically learning and improving from experience without being explicitly programmed for a specific problem, but for a generic type of problem. This article approaches the different applications of ML in a series of econometric methods. *Objective*: The objective of this research is to identify the latest applications and do a comparative study of the performance of econometric and ML models. The study aimed to find empirical evidence for the performance of ML algorithms being superior to traditional econometric models. The Methodology of systematic mapping of literature has been followed to carry out this research, according to the guidelines established by [39], and [58] that facilitate the identification of studies published about this subject. *Results*: The results show, that in most cases ML outperforms econometric models, while in other cases the best performance has been achieved by combining traditional methods and ML applications. *Conclusion*: inclusion and exclusions criteria have been applied and 52 articles closely related articles have been reviewed. The conclusion drawn from this research is that it is a field that is growing, which is something that is well known nowadays and that there is no certainty as to the performance of ML being always superior to that of econometric models.

Keywords: machine learning, econometric models, regression, prediction

1 Introduction

The concept of "Econometry", was first introduced by Pawel Ciompia at the beginning of 20th century. After him, Jan Tinbergen, was one of the first researchers to apply mathematics in the testing of economic hypotheses [71]. Econometrics combine elements of economics, mathematics and statistics. The statistical methods used in econometric models are specifically targeted at this domain and therefore they are non-applicable to other statistical fields [28]. The purpose of machine learning is to solve real-life problems by automatically learning and improving from experience without being explicitly programmed for a specific problem, but for a generic type of problem. Thanks to global economic interdependence, nowadays much more information is available for predictions. These large amounts of data require different types of methods for optimal information processing. As shown in Figure 1, this research comprehends the nature and the growing interdependence of economics, mathematics and computer science.

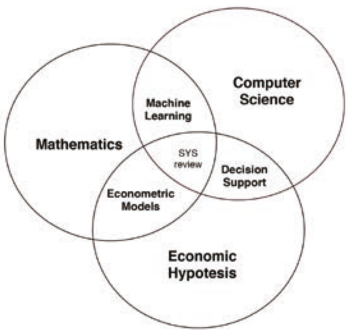


Figure 1. Fields that converge in that SMS.

Therefore, traditional economic models and applications require tools that have a greater computing capacity and new forecasting methodologies that will provide more accurate predictions. In the field of prediction, the ML algorithms based on a previously identified label are classified as supervised ML algorithms [42]. Supervised algorithms look for functions that predict well outside the sample. Economists would denominate this as the dependent variable; the one that will change depending on the changes in other variables. If the labeled attribute does not exist, an unsupervised algorithm is necessary for data exploration rather than the prediction of results. For instance, one could try to predict the value "y" of a company from its observed characteristics "x". Within the field of supervised algorithms there are many different applications that can be employed [12], either for classification or regression. Let's suppose we set out to measure whether having a gym in the workplace would improve the employees' efficiency (where productivity was measured as projects completed per month in a 40 hours work week). Economists would seek for a logical experiment that might entice certain workers to use gym facilities for reasons unrelated to their current productivity (i.e., temporary gym at the workplace). We can estimate a model using a linear regression as shown in the Figure 1:

$$Y_i = \alpha + \beta_0 + \beta_1 X_i + \varepsilon_i \tag{1}$$

or a multiple linear regression as in equation 2:

$$Y_i = \alpha + \beta_0 + \sum \beta_p X_{pi} + \varepsilon_i \tag{2}$$

where Y_i is the outcome (the productivity of the individuals within a year), X_i is the policy of interest (in case the worker has gone to the gym), β is the key parameter of interest (the effect of going to the gym within the working hours), α denotes the other parameters, and ε_i is an error term. Using the same data, a ML approach would involve identifying the variables that are strictly associated with productivity. This is due to the wide range of potential indicators in the data, and the likelihood of building a model that would predict the profitability well, either inside or outside the sample data.

ML models have the capacity to overcome those econometric regression models according to different prediction rules that underlie the systems [48]. The possibilities offered by ML have led several researchers in financial econometrics to carry out comparative studies on the performance of ML applications against traditional models as suggested [45]. However, the two approaches have not always been in conflict with each other. For instance, if just one subset of control variables is predictive, a ML model selection approach could help target the most relevant one. Data mining methods can also be helpful if there are significant interaction effects, so one is focused on predicting effects for certain individuals instead of an overall impact for the whole population [7].

This research work analyzes the state of the art and identifies ML studies that are oriented to econometric models. It is developed under a methodology for the systematic mapping of literature, following the guidelines established by [57, 58], and [41] for carrying out *Systematic Mapping Studies* (SMS). Thanks to this type of SMS it is possible to categorize existing studies in a specific area of research through an outline and structure that indicate how often investigations are conducted in that area. The results of the study are represented visually on a map [51].

The remainder of this study is organized as follows: Section 2 analyzes the state-of-the-art reviews and the surveys performed by other authors in the fields of econometrics and ML. Then, Section 3 details the stages of the systematic mapping study methodology proposed by [58]. In Section 4 the results of the report stage of the conducted systematic mapping study are outlined. In Section 5 results are analyzed in detail. Finally, the conclusions from the conducted research are described in Section 6.

2 Related Work

In recent years, many authors have presented reviews of ML applications in econometric fields. [48], and [3] published theoretical results that emphasised the range of prediction possibilities offered by ML in the field of economics. Since econometrics includes many applications some authors have narrowed down the scope of their studies. For instance, [4] highlights the main machine learning models that are applied in econometric models, including methods based on regression, classification, unsupervised learning methods and matrix completion methods, other authors explore concrete areas of machine learning applications in econometrics, such as methods for demand estimation [6]. Moreover, others conducted an in-depth examination of the major machine learning models for time series forecasting [1, 32] made comparative studies and conclusions derived from traditional and machine learning applications in financial market forecasting. Other comparative studies that have pointed to the good performance of machine learning worked in detecting irregular patterns and making short term forecasts using heterogeneous data [44]. According to [58], SMS studies aim to identify principal studies in the area of interest, more extensive definition of what a SMS is will be given in the following Section 3. Since there are many articles in this field, and some of them mentioned in the previous paragraph, a SMS of the published articles has been carried out. SMS is a methodology that intends to standardize and to objectively review different topics. ML algorithms and their applications are a growing field of study [67, 68] which has many effects in the worldwide economy [23] and therefore, the authors find it interesting to combine all the information with the different applications that have been made, especially at the level of regressions. The authors have found it interesting to create a word cloud with all the titles collected from the searches in order to see quickly which are the topics on which the articles related to this topic mainly focus. The areas covered by the real-world ML applications in traditional econometric models are described in Figure 2.

Figure 2. Word cloud from the titles of all the articles collected in the review.

3 Research Methodology

To complement the definition of SMS given in the previous section, a SMS is defined as a secondary study aimed at identifying if there are scientific evidence and research contributions in a field or specific research area. SMS allows researchers to get an overview of the amount of scientific evidence on the subject under investigation. Several authors have defined procedures or guidelines for conducting a SMS [57, 58, 40]. Some of the main benefits of a SMS are described as follows:

– Uses an objective and validated procedure to identifying papers or relevant information in a specific research field.

– Helps identify future lines of research arising from the information gaps identified in the mapping process.

– The emergence of new research that can be used in future systematic literature reviews.

In the present article, the SMS methodology and phases have been followed as proposed in the review of [58], and [39]. The process has been organized into three phases: planning, development and mapping report. The schema of those three phases is presented in Figure 3 and will be described in detail in the subsections that follow. All the papers included in the review are listed in Table 9.

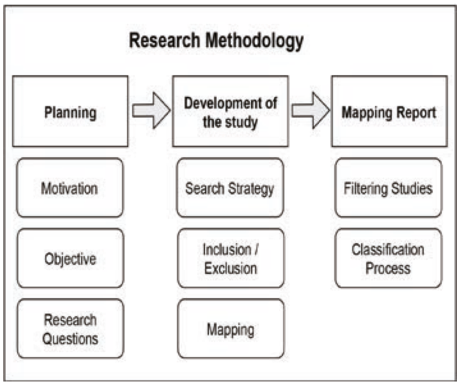


Figure 3. SMS methodology phases that will be described in detail in following subsections.

3.1 Planning

For the planning of our SMS, the following three activities have been considered: Motivation, Objective and Research Questions. For the planning of the activities, the works of [39, 58] have been used as reference. Those activities are described in more detail below;

3.1.1 Motivation

The evolution and adoption of machine learning in the field of traditional econometric models motivated this SMS. The main motivation of this paper is the review of existing papers on the application of machine learning techniques in traditional econometric models, as well as the comparison of their results. The identification of future lines of research in this area is also the motivation behind this study.

3.1.2 Objective

In recent years, it has been possible to develop many models applied to economic problems. All this thanks to the rapid growth of machine learning applications which has been driven by the high demand for real-time applications in real-world scenarios. The objective of this research is to identify the latest applications and do a comparative study of the performance of econometric and machine learning models. The study aimed to find empirical evidence if machine learning algorithms obtain better results than econometric models when compared to the same problem, or on the contrary, in this field so far there is evidence that when machine learning and econometric models are used together is it possible to achieve better results.

3.1.3 Research Questions

Defining research questions helps find the evidence required for the study. These questions will allow to categorize the literature published until June 22, 2020 and to present visual maps in the results section. This SMS is based on the following research questions:

– **RQ1** - How and in which fields machine learning has been implemented as econometric model applications?

– **RQ2** - How does supervised machine learning complement traditional econometric models?

– **RQ3** - Comparing machine learning and econometric models what are the most frequently applied methods, and in what study context?

3.2 Development of the Study

This Section describes the process followed to address the SMS. First the search strategy has been defined to obtain relevant papers. The inclusion / exclusion criteria have been numbered and used to select the studies to be mapped. In this case, a large number of articles were identified as noise and the process has been conducted individually as suggested by the author in [59].

3.2.1 Search Strategy

To conduct a SMS, it is important to build a search strategy and define a search string, even though some authors have concluded that it not possible to prevent bias in systematic reviews [74]. To minimize the possible bias in research, the authors have used PICO (Population, Intervetion, Comparision and Outcomes) guidelines defined by [41, 40] and applied in [58]. PICO was recently referred to as a good set of practical guidelines for conducting SMS [20]. The authors of [59] proposed the PICOC model which has been developed within the PICO framework and its Context has been extended. Nevertheless, in this case, only the PICO framework has been used.

– Population: The identified papers.
– Intervention: The methods implementing machine learning and traditional econometrics.
– Comparison: The different types of results are compared.
– Outcomes: Complementarities and uses of econometric and machine learning models

After applying the PICO approach, our keywords are *econometric* and *ML*. To reduce the search and obtain more accurate results, the keywords considered in the second search were closely related to the research *Regression*, and *Supervised*. The selection of those databases done has been according to the volume of articles as well as the variety of publication topics, being among those selected those recommended as optimal for this type of analysis [10]. The search strings were built for the following databases: Web of Science, Scopus and Springer. The search was restricted to June 22, 2020. Three search strings were designed for each database to reduce the number of articles obtained in the preliminary results, those have been represented in Table 1. In the creation of the search strings, due to the fact that the second condition proved to be very restrictive, as it yielded very few articles, it was decided to extend it a little further by including the possibility of a new word. The number of articles per year found for each of the search engines are those described in the Table 2.

3.2.2 Inclusion/Exclusion Criteria

Regarding the inclusion and exclusion criterias, [58] pointed the importance of establishing the characteristics that the identified studies must meet in order to be included or excluded from a systematic mapping study. Using the [58] guide as a basis, the following inclusion and exclusion criteria were considered when selecting a paper. Those criterias are the ones that have been described in Table 3.

3.3 Mapping Report

The mapping report includes the filtering studies and classification process descriptions. During the filtering process, the relevance of 4 of the papers has been questioned and therefore have been removed from the overall study. To strengthen the criteria for the inclusion-exclusion of articles, the support of three researchers was requested for evaluation by experts. Moreover, this has allowed us to maintain neutrality and objectivity in the process of selection and rejection of articles related to the subject of the review. The full mapping report is shown in Table 9.

3.3.1 Filtering Studies

From the three search strings defined, a total of 356 related studies were found in the first step. To filter all the studies, the previously defined inclusion and exclusion criteria have been applied. The filtering process was conducted by the first author. The papers that have been selected met all the inclusion criteria and none of the exclusion criteria. The first author consulted the rest of the co-authors in cases where it was not clear whether an article should be included or excluded. The authors have requested support from other researchers to resolve disagreements between them when needed.

3.3.2 Classification Process

Once the filtering process has been completed, the selected articles were classified on a spreadsheet into the following categories: Author, Title, Year, Type of Publication, Machine learning vs econometric, Field of application, Research Type, Evolution Activity and contribution Type. The *Type of Publication* is divided into; Journal, Conference and Book Chapter. The *machine learning vs econometric*; describes the output in terms of the performance achieved by machine learning and the econometric models, it is stated if one performed better than the other or if they were used jointly. The

Table 1. Search string designed for database search. The articles have been extracted directly from each Search Engine.

Data Base	Search String
Web of Science (WS1)	((TS=(Econometric AND Machine Learning))) AND LANGUAGE: (English)
Web of Science (WS2)	((TS=(Econometric AND Machine Learning AND supervised))) AND LANGUAGE: (English)
Web of Science (WS3)	((TS=(Econometric AND machine AND learning AND regression OR supervised))) AND LANGUAGE: (English)
Scopus (SC1)	TITLE-ABS-KEY (”Econometric”) OR TITLE-ABS-KEY (”Machine Learning”)) AND TITLE-ABS-KEY (”*supervised learning*”) AND (TITLE-ABS-KEY (”Econometric*”) OR TITLE-ABS-KEY (”regression*”)) AND (LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016)) AND (LIMIT-TO (LANGUAGE , ”English”))
Scopus (SC2)	TITLE-ABS-KEY (”Econometric”) AND TITLE-ABS-KEY (”Machine Learning”)) AND TITLE-ABS-KEY (”supervised*”) AND (LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016)) AND (LIMIT-TO (LANGUAGE , ”English”))
Scopus (SC3)	TITLE-ABS-KEY (”Econometric”) AND TITLE-ABS-KEY (”Machine Learning”)) AND TITLE-ABS-KEY (”*economet*”) OR TITLE-ABS-KEY (”supervised*”) OR TITLE-ABS-KEY (”regression*”) AND (LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016)) AND (LIMIT-TO (LANGUAGE , ”English”))
Springer (SP1)	(”Econometric”) AND (”Machine Learning”)
Springer (SP2)	(”Econometric”) AND (”Machine Learning”) AND (”supervised”)
Springer (SP3)	(”Econometric”) AND (”Machine Learning”) AND (”supervised”) OR (”regression”)

Table 2. Number of articles per year under each search engine criteria. The number of articles in 2020 is only till June 22nd 2020.

	2016	**2017**	**2018**	**2019**	**2020**
SC1	89	129	212	382	162
SC2		2	1	2	
SC3	9	30	28	52	19
WS1	5	12	16	29	11
WS2				2	
WS3	3	6	5	15	4
SP1	129	147	227	315	355
SP2	28	26	46	80	81
SP3	15	17	35	55	63

Table 3. Inclusion and Exclusion Criterias

Inclusion	**Exclusion**
IC1: Peer-reviewed book chapters and papers published in journals or conferences	EC1: Duplicated papers
IC2: Studies published between 2016 to June 2020	EC2: Papers that are not related to machine learning and econometric applications
IC3: Studies in the field of machine learning applications in econometrics	EC3: The papers in which the authors have not identified an econometric and machine learning application (event joint or replaceable methodologies)

Field of application is the field to which the algorithm has been applied (ie: Stock market, Agriculture,...). In the *Research Type category*, studies are classified into: Evaluation research, Validation research, Solution proposal, Philosophical paper, Experience report, and Opinion paper. The *Evolution activity* allows for the classification of the articles determining the following categories; Validate, Implement or Analyse, which means if only an analysis had been carried out in the research or if it implemented and validated a proposed solution. The *Contribution type* consists of the main contribution of the article: Method, model, framework, or platform. There is a set of articles that can contain two or more research types, in those cases, a single record containing the categories is made to avoid the duplicity of the data. The classifications and categories are being presented according to the classification described by [39].

4 Mapping

For each of the databases: Springer, Scopus, and Web of Science, a first simple search string was defined using only machine learning and econometrics as keywords, and 2884 papers appeared in the search results. For this reason, the authors decided to extend the search string by increasing the number of keywords, with a second search string detailed in Table 1. The total number of article results was 268, nevertheless, the results were too strict and not covering the whole expected searches. Therefore, it was decided to expand the search string a little more by extending the concept. The application of the last search chain resulted in 356 papers which were reviewed and filtered by applying the inclusion and exclusion criteria.

That the papers were excluded if they did not meet the inclusion criteria established in the Methodology for the development of the SMS and that have been described in the 3.2.2. The final result is the one shown in Figure 4. As can be seen in the diagram 4, 51 articles were duplicated papers. Then there were 111 articles that contained machine learning and econometrics but not related to both files, and finally, 142 articles were removed because the aim of the study was to identify those papers that were comparing experiments implementing machine learning and econometric models. The final number of articles that have been selected to conduct the research has been 48.

4.1 General Analysis

Due to the variable and extensive nature of research, a graphical analysis of the fields in which this type of research is published is given in Figure 4.1. All the articles from the first search string have been taken so that the volume in terms of the distribution of the publications was wide. The scope of journals that contain most of the publications in the research field of econometric models and machine learning are the ones in computer science and economics. Nevertheless, there are also publications in mathematics and engineering journals, which can be considered essential fields of knowledge when conducting this type of research.

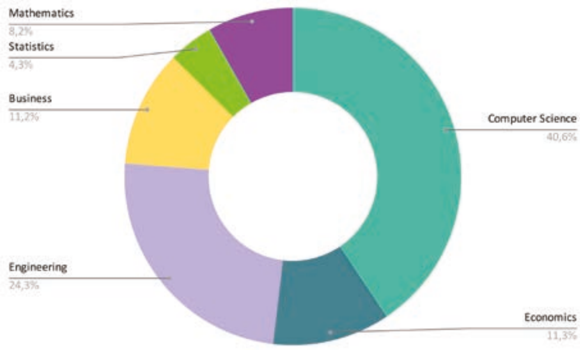


Figure 5. Fields of the journals where the articles have been published. The percentages correspond to the total sample on the first search String created.

5 Results

The results of the systematic mapping are shown in Figure 5. In Figure 5, three dimensions of the previous dimensions described in Section 3.3.2 where the classification process is described have been considered. Those dimensions are: Contribution type, ML vs econometrics, and Research type according to the guidelines for bubble plot graphs, defined by [57]. In the systematic mapping review, the validation of the different models has considered the most important element of the researches, as shown in the table. The different tables are evaluated in Table 4 under Method, 5 Model, and 6 Framework.

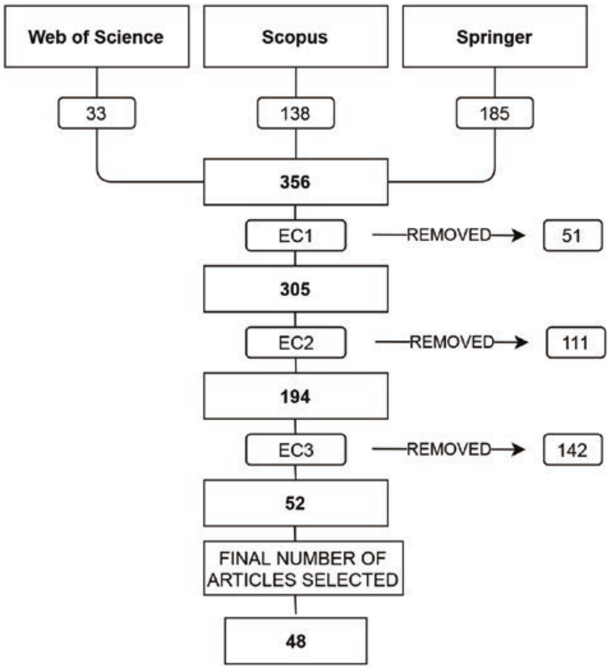


Figure 4. Exclusion Criteria applied to the total articles extraction

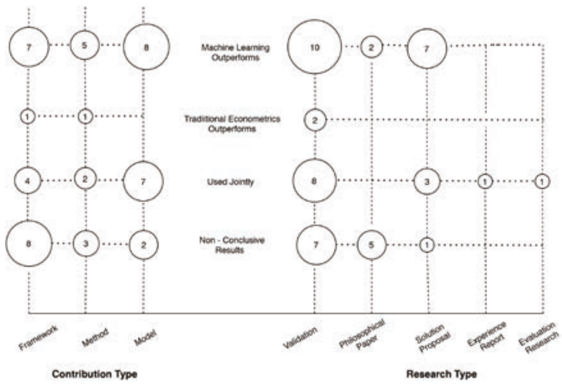


Figure 6. Mapping study

5.1 RQ1 - How and in what fields ML has been implemented as econometric model applications?

The results derived from RQ1 are shown as a stacked bar graph in the Figure 7. As seen in the graph, the articles have been classified into large activity groups into which the research articles could be categorized. A sector of activity has been kept as theoretical due to the fact that some articles were very theoretical and generic in terms of activity leading to an impossibility to adjust it to one sector of activity or another. As can be seen in the graph, the analysis of future performance is oriented to all industries, while the analysis of time series is mostly used in the stock market and investment applications. One of the issues where it is practically a common denominator in all cases is the forecast of future prices.

5.2 RQ2 - How does Supervised ML complement traditional econometric Models?

To answer this question, 4 different hypotheses have been presented as shown in Table 7. In Table 8 the results are shown regarding the differences in the methods, model and framework and in the cases where the machine learning techniques or econometric models outperform one another. In the majority of the cases where machine learning and traditional econometric models were compared, machine learning has performed better in making predictions. There are some situations where the highest accuracy is achieved by using the algorithms jointly, as presented in Table 8. This Table shows that in cases where a new model is proposed, the highest accuracy is achieved when the models are combined, indicating that machine learning models or econometric models do not necessarily work better than each other but that the synergy between both is usually the best option due to the nature of both models. This classification should be placed in the framework of considering that this SMS considers articles from 2016, in which machine learning was already an established field.

Table 4. Articles with Contribution type classified as "Method". ANN: Artificial Neural Network, ARIMA: Autoregressive integrated moving average, D-ML: Diverse ML Methods, LR: Linear Regression, MLR: Multinomial logistic regression, NN: Neural Network, RF: Random Forest, SARIMA: Seasonal Autoregressive Integrated Moving Average, SCL: Supervised Classification algorithms, SVR: Support Vector Regression, SVM: Support Vector Machine, TS: Time Series

Author	ML vs Eco	ML Algorithms	Econometric models	Topic	Output
[17]	Eco Outperforms	RF	MLR	Agriculture	Future Demand
[31]	ML Outperforms	RF/NN	ARIMA	Energy	Future Price
[29]	ML Outperforms	ANN	SARIMA	Energy	Future Price
[56]	ML outperforms	ML	Regression	Tourism	Future performance
[14]	ML Outperforms	ANN	LR	Agriculture	Future Performance
[62]	Used Jointly	ANN	ARIMA	Energy Price	Time Series
[29]	Non Results	ANN	ARIMA	Citizien	Future Performance
[38]	Used Jointly	SCL	LDA	Health	Future Performance
[5]	Non Results	SVR/NN	ARIMA	Theorical	Future Performance
[75]	Non Results	SVM	Theorical	Theorical	Future Performance
[36]	Non Results	NN	TS	Citizienship	Future Performance

Table 5. Articles with Contribution type classified as "Model". ARIMA: Autoregressive integrated moving average, DL: Deep Learning, DNN: Deconvolutional Neural Network, D-ML: Diverse ML Methods, FE -R: Fixed Effect Regression, GA: Genetic Algorithm, GARCH: Generalized AutoRegressive Conditional Heteroskedasticity, KNN: k-nearest neighbors algorithm, LASSO: east absolute shrinkage and selection operator, LR: Linear Regression, NN: Neural Network, SVR: Support Vector Regression, PCA: Principal Component Analysis, PCR: Put-call ratio, RF: Random Forest

Author	ML vs Eco	ML Algorithms	Econometric models	Topic	Output
[66]	ML Outperforms	GA	ARIMA	Citizien	Future Price
[21]	Used Jointly	SVR	ARIMA	Investment	Time Series
[49]	Used Jointly	RNN	GARCH	Agriculture	Future Performance
[33]	ML Outperforms	KNN,..	Regression	Agriculture	Future Demand
[25]	Non results	PCA	LR	Investment	Future Performance
[54]	Non Results	GA	HODRICK-PRESCOTT	Stock Market	Future Price
[60]	Used Jointly	SVR	LASSO	Transport	Future Demand
[26]	Used Jointly	RF	FE-R	Trade	Future Performance
[46]	Used Jointly	DL	Regression	Tourism	Future Performance
[53]	ML outperforms	SVR/KNN	PCR	Tourism	Future Price
[72]	ML outperfoms	AVM ML	Regression	investment	Theorical
[22]	ML outperfoms	ANN	Regression	Tourism	Future Demand
[2]	ML outperfoms	DNN	ARIMA	Investment	Future Price
[27]	Used Jointly	SVR	LASSO	Transport	Future price
[47]	ML outperforms	NN	ARIMA	Investment	Future Price
[69]	Used Jointly	D-ML	Regression	Theorical	Theorical

Table 6. Articles with Contribution type classified as “Framework”. ANN: Artificial Neural Network, ARIMA: Autoregressive integrated moving average, BA:Bootstrap aggregating, GARCH: Generalized AutoRegressive Conditional Heteroskedasticity, DNL: Deep Neural Learning, DT: Decision Tree, D-ML: Diverse ML Methods, LSTM: Long short-term memory, NLP: Natural Language Processing, NN: Neural Network, PCA: Principal Component Analysis, RF: Random Forest, RNN: Recurrent neural network, RT: Regression Tree, SVM: Support Vector Machine, SVR: Support Vector Regression

Author	ML vs Eco	ML Algorithms	Econometric models	Topic	Output
[11]	ML Outperforms	NA	Arima	Investment	Future Performance
[35]	Eco Outperforms	SVR/NN	regression	Stock Market	Future price
[44]	Used jointly	RT,BA	Regression	Film Industry	Future Performance
[64]	Used Jointly	ANN	Barndorff-Nielsen and Shephard	Investment	Future Performance
[24]	Non results	RF	Regression	Tourism	Future Performance
[76]	ML outperforms	NN/RF	ARIMA / Garch	Transport	Future price
[52]	Used Jointly	NLP	Regression	Banking	Future price
[19]	Used Jointly	ML	DF	Theorical	Future performance
[13]	ML outperforms	PCA	Regression	Banking	Future performance
[9]	ML outperforms	D-ML	Multivariate Regresison	Theorical	future performance
[55]	ML outperforms	D-ML	Regresison	Insurance	Future Performance
[48]	Non Results	D-ML	Multivariate Regresison	Theorical	future performance
[37]	ML outperforms	D-ML	Regressison	theorical	Future Performance
[30]	Non Results	D-ML	ARIMA	theorical	Future Performance
[43]	Non Results	D-ML	Bayesian Methods	theorical	Future Performance
[63]	Non Results	DNL	Regresison	Theorical	Future Performance
[16]	Non Results	D-ML	Regresison	Theorical	Future Performance
[8]	Non Results	D-ML	Multivariate Regresison	Theorical	Future performance
[3]	Non Results	ML	Regression	Theorical	Future performance
[18]	Non Results	RNN,LSTM	Regressions	Investment	Future performance

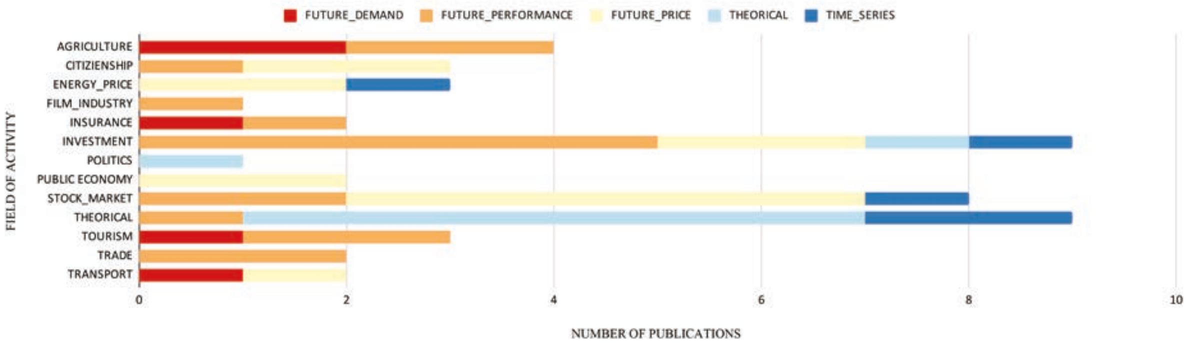


Figure 7. Fields per contribution type

Table 7. Classification according the 4 different hypotheses presented

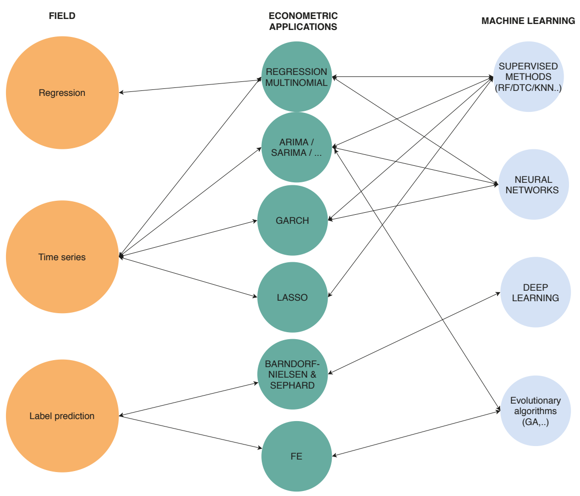
Name	Description
Used Jointly	Combination of Econometric Models and ML algorithms
ML Outperforms	Comparision where ML algorithms achieve better results versus Econometric Models
ECO Outperforms	Comparision where Econometric Models achieve better results versus ML algorithms
No Results	Non Conclusive Results

Table 8. Results in difference

	Used Jointly	ML Outperforms	ECO Outperforms	No results
Method	[38], [62]	[15], [31], [29], [14], [56]	[17]	[36], [5], [75]
Framework	[52], [44], [64], [19]	[11],[55], [37], [48], [9], [76], [13]	[35]	[3], [24], [30], [63] [43] , [16] [18], [8]
Model	[21], [70], [49], [46], [60], [26], [27]	[66], [47],[33], [2], [64], [53], [72], [22]		[25], [54]

5.3 RQ3 - Comparing ML and Econometric Models what are the most frequently applied methods, and in what study context?

Figure 7 compared the algorithms and their applications in econometrics and machine learning. In some cases their performances are contrasted, in others, they are used jointly. The most research methods are ANN and RF vs ARIMA and different types of regression (and the different variants that it can have).



6 Conclusions

Overall, new technologies and applications, such as machine learning, help increase the accuracy of prediction algorithms. A SMS serves to have an overview of the state of the art in the field, this review shows that in terms of the number of publications, this field is growing and more and more innovative and joint models are beginning to emerge, offering better prediction capabilities. In the case of this SMS, it has been observed that there are more than 300 articles in which the two topics are related, however, when it comes to directly compare the two, the number of articles is even smML applications and econometric modelsaller. Taking into account the search criteria of this article, the trend and the highest degree of innovation, as well as the number of articles published, the stock market is where there are more applications of machine learning in econometrics. Taking into account the results of this SMS, there are many possibilities for future lines of research, where econometric models could be combined with supervised machine learning models, and open a new paradigm for the creation and implementation of hybrid models. In addition, other possible future lines of research would be to analyze in more detail some specific sectors of activity in which most of the publications are growing, in which various types of machine learning applications and econometric models converge. An example of these types of activity could be the investment sector (both private equity and securities). Another interesting approach would be to identify

Table 9. ML vs ECO: Machine Learning Algorithm Vs Econometric Model, Publication = Type of Publication, Topic = Field of application, Research = Type of Research, Contribution = Contribution Type, Activity = Evolution Activity

Authors	Title	Year	Publication	ML vs ECO	Topic	Research	Activity	Contribution
[17]	Determinants of credit demand of farmers in Lam Dong, Vietnam: A comparison of Machine Learning and multinomial logit	2019	Article	ECO	Agriculture	Validation	Validate	Method
[15]	Alternative prediction Methods in the stock exchanges of Thailand	2019	Conference	ML	Stock Market	Validation / Solution Proposal	Validate	Method
[31]	Long-term forecast of energy commodities price using Machine Learning	2019	Article	ML	Energy Price	Validation	Validate	Method
[66]	Learning from man or machine: Spatial fixed effects in Urban Econometrics	2019	Article	ML	Citizienship	Validation	Conceptual	Model
[55]	A case study on reducing auto Insurance attrition with Econometrics, Machine Learning, and A/B testing	2019	Conference Paper	ML	Insurance	Experience	Validate	Framework
[11]	The effect of information asymmetries on serial crowdfunding and campaign success	2018	Article	ML	Investment	Validation / Solution Proposal	Analyse	Framework
[33]	Can Machine Learning improve prediction - An application with farm survey data	2018	Article	ML	Agriculture	Validation	Analyse	Model
[8]	The great regression Machine Learning, Econometrics, and the future of quantitative social sciences	2018	Article	Non Results	Theorical	Philosophical	Analyse	Framework
[48]	Machine Learning: An applied Econometric approach	2017	Article	ML	Urban	Philosophical	Analyse	Framework
[37]	Some comments on the current state of Econometrics	2016	Article	ML	Theorical	Philosophical	Analyse	Framework

[61]	Advances in Time Series Analysis and Forecasting	2017	Chapter	ML	Stock Market	Solution	Implement/ Validate	Model
[25]	Empirical Economics	2019	Article	Non Results	Investment	Validation	Implement/ Validate	Model
[16]	Illustrating Statistical Procedures: Finding Meaning in Quantitative Data	2020	Chapter	Non Results	Theorical	Philosophical	Analyse	Framework
[29]	Neural Computing and Applications	2019	Article	ML	Energy Price	Validation / Solution Proposal	Implement/ Validate	Method
[9]	Mathematical and Statistical Methods for Actuarial Sciences and Finance	2018	Chapter	ML	TRADE	Validation	Implement, Validate	Framework
[18]	A Multivariate and Multi-step Ahead Machine Learning Approach to Traditional and Cryptocurrencies Volatility Forecasting	2019	Chapter	Non Results	Stock Market	Validation	Implement, Validate, Analyze	Framework
[63]	Regional Policy Analysis in the Era of Spatial Big Data	2020	Chapter	Non Results	Politics	Philosophical	Analyse	Framework
[36]	Comparative analysis of time series model and machine testing systems for crime forecasting	2019	Article	Non Results	Citizienship	Validation	Implement / Validate	Method
[54]	A novel hybrid model based on Hodrick–Prescott filter and support vector regression algorithm for optimizing stock market price prediction	2017	Article	Non Results	Stock Market	Validation / Solution Proposal	Implement, Validate, Analyze	Model
[62]	A wavelet-based hybrid neural network for short-term electricity prices forecasting	2020	Article	Used Jointly	Energy Price	Validation / Solution Proposal	Implemenr / Validate / Analyze	Method
[50]	Beyond Traditional Probabilistic Methods in Econometrics	2019	Chapter	Non Results	Theorical	Philosophical	Analyse	Framework
[30]	Online workload forecasting	2017	Chapter	Non Results	Theorical	Philosophical	Analyse	Framework
[52]	Computational Data Sciences and the Regulation of Banking and Financial Servicesk	2017	Chapter	Used Jointly	Investment	Validation / Solution Proposal		Framework

[2]	Deep learning and wavelets for high-frequency price forecasting	2018	Chapter	ML	Stock Market	Validation	Implement, Validate, Analyze	Model
[5]	Multistep-ahead prediction: A comparison of analytical and algorithmic approaches	2018	Chapter	Non Results	Theorical	Validation	Implement, Validate, Analyze	Method
[21]	A Machine Learning approach to univariate time series forecasting of quarterly earnings	2020	Article	Used Jointly	Investment	Validation	Implement, Validate, Analyze	Model
[49]	Integration of RNN with GARCH refined by whale optimization algorithm for yield forecasting: a hybrid Machine Learning approach	2020	Article	Used Jointly	Agriculture	Validation / Solution Proposal	Implement, Validate, Analyze	Model
[3]	Machine Learning Methods That Economists Should Know about	2019	Article	Non Results	Theorical	Validation		Framework
[35]	Machine Learning versus Econometric jump models in predictability and domain adaptability of index options	2019	Article	Eco	Stock Market	Validation	Analyse	Framework
[14]	Comparative decision models for anticipating shortage of food grain production in India	2018	Article	ML	Agriculture	Validation	Analyse	Method
[75]	Spatial Choice Modeling Using the Support Vector Machine (SVM): Characterization and Prediction	2018	Chapter	Non Results	Investment	Validation	Analyse	Method
[44]	Machine Learning versus Econometrics: prediction of box office	2019	Article	Used Jointly	Film Industry	Validation	Analyse	Framework
[65]	Refinements of Barndorff-Nielsen and Shephard model: an analysis of crude oil price with Machine Learning	2020	Article	ML	Investment	Validation		Model
[73]	Data science: the impact of statistics	2019	Article	Used Jointly	Theorical	Experience	Analyse	Framework

[69]	Causal tree with instrumental variable: an extension of the causal tree framework to irregular assignment mechanisms	2019	Article	Used Jointly	Investment	Evaluation	Implement, Validate, Analyze	Model
[38]	Data Science	2017	Chapter	Used Jointly	health	Validation	Implement, Validate	Method
[46]	Stacked autoencoder with echo-state regression for tourism demand forecasting using search query data	2018	Article	Used Jointly	Toruism	Validation	Validate	Model
[24]	Real-time inflation forecasting with high-dimensional models: The case of Brazil	2017	Article	Non Results	Public Economy	Validation	Analyse	Framework
[53]	Hedonic Housing Theory - A Machine Learning Investigation	2017	Article	ML	Investment	Validation / Solution Proposal		Model
[60]	Forecasting transportation demand for the US market	2019	Article	Used Jointly	Transport	Validation		Model
[26]	Optimal retail location: Empirical Methodology and application to practice	2019	Article	Used Jointly	Trade	Validation		Model
[76]	Comparison of Econometric Models and Artificial Neural Networks Algorithms for the Prediction of Baltic Dry Index	2019	Article	ML	Transport	Validation	Analyse	Framework
[27]	The Informational Content of the Term Spread in Forecasting the US Inflation Rate: A Nonlinear Approach	2017	Article	Used Jointly	Public Economy	Validation	Validate	Model
[56]	Economic crises and market performance-A machine learning approach	2017	Article	ML	Tourism	Validation	Analyse	Method
[72]	Who performs better? AVMs vs hedonic models	2020	Article	ML	Investment	Validation / Solution Proposal	Proposal	Model

[22]	Artificial Neural networks-based Econometric models for tourism demand forecasting	2017	Conference	ML	Tourism	Validation / Solution Proposal	Proposal	Model
[34]	An Introduction to the NMPC-Graph as General Schema for Causal Modeling of Nonlinear, Multivariate, Dynamic, and Recursive Systems with Focus on Time-Series Prediction	2016	Conference	Non Results	Theorical	Philosophical		
[19]	Batch and incremental dynamic factor Machine Learning for multivariate and multi-step-ahead forecasting	2019	Article	Used Jointly	Theorical	Validation	Implement	Framework
[13]	Nowcasting and forecasting GDP in emerging markets using global financial and macroeconomic diffusion indexes	2019	Article	ML	Public Economy	Validation	Analyse	Framework
[47]	Advances in Time Series Analysis and Forecasting	2017	Chapter	ML	Stock Market	Solution Proposal	Implement	Model

which methods from other scientific fields, for example focusing research on applications of genetic algorithms or deep learning.

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8 Conflicts of interest

The authors declare no conflict of interest.

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