Machine Learning versus Fundamental Investment Analysis: A Meta-Analysis

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ABSTRACT,
The performance of machine learning algorithms in financial asset pricing is assessed through a meta-analysis in which the results of previous research is combined. The meta-analysis consisted of a research sample of 63 research papers on the application of machine learning algorithms in stock pricing, option pricing, and bond pricing. The 63 research papers aided in accepting the three sub-hypotheses, that machine learning algorithms are associated with higher pricing performance than traditional financial asset pricing tools, and the main hypothesis, that machine learning algorithms outperform fundamental investment analysis.

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Keywords
Machine learning, stock pricing, option pricing, bond pricing

1. INTRODUCTION

The pricing and valuation of financial assets remains one of the most difficult tasks in finance. Investors worldwide are in a ongoing search for the best financial assets for their investment portfolios. In the past, multiple mathematical models have been introduced to aid investors in this search. Sharpe, Lintner, and Treynor introduced the CAPM in the early 60s for the calculation of an asset's expected return (Sharpe, 1964) (Lintner, 1965) (Treynor, 1961), Fama & French introduced the Fama-French multifactor models as another tool for the calculation of an asset's expected return (Fama & French, 1993), and Black & Scholes developed the Black-Scholes method for pricing options (Black & Scholes, 1973). As a result of the 2008 financial crisis, many investors are looking beyond these traditional investment analysis methods. The massive increase in data in the last decade and the fact that machine learning algorithms have proven to be more effective than traditional statistical techniques in many other fields outside finance, have led researchers to investigate the application of machine learning in finance (Rasekhschaffe & Jones, 2019). The improvement of machine learning over fundamental investment analysis is that machine learning algorithms have the ability to learn from past financial data to improve future pricing performance (Das & Behera, 2017). Next to the inclusion of massive amounts of past data, machine learning opens the door to the inclusion of non-traditional data in price forecasting, such as semantics in social media and financial reports (Ndikum, 2020). The increase of research in machine learning in financial asset pricing has led to the discussion whether machine learning produces better pricing forecasts than fundamental investment analysis tools such as the Black-Scholes method. This research paper focuses on previous research on the application of machine learning algorithms in stock pricing, option pricing, and bond pricing. The goal of the research paper is to combine findings of existing research to conclude whether machine learning algorithms outperform fundamental investment analysis tools.

The research question is: do machine learning algorithms outperform fundamental investment analysis? The expectation is that, due to its ability to process massive amounts of datasets for financial asset analysis, machine learning does outperform fundamental investment analysis in all cases. This hypothesis will be tested through a meta-analysis on previous research on the application of machine learning in three sub-divisions of fundamental investment analysis: stock pricing, option pricing, and bond pricing. This leads to three sub-hypotheses:

- H1: Machine learning algorithms are associated with higher pricing accuracy than traditional stock pricing methods
- H2: Machine learning algorithms are associated with higher pricing accuracy than traditional option pricing methods
- H3: Machine learning algorithms are associated with higher pricing accuracy than traditional bond pricing methods

In the following sections, first, the concept of machine learning will be discussed through the three most in literature encountered machine learning methods, namely Artificial Neural Networks, Random Forests, and Support Vector Machines. Second, the three earlier mentioned subdivisions of fundamental analysis and their existing pricing models will be discussed. After the background of machine learning and fundamental investment analysis is given, the results of the meta-analysis will be discussed. Finally, with the results of the meta-analysis, the conclusion can be stated and the hypotheses can be either accepted or rejected.

2. MACHINE LEARNING

In literature, there is a large variety in definitions on the concept of machine learning. Das and Behera state that machine learning is a paradigm that may refer to learning from past experiences to improve future performance (Das & Behera, 2017). According to Ndikum, machine learning algorithms are prediction algorithms designed to deal with large volume, high dimensionality and unstructured data used in an enormous number of fields (Ndikum, 2020). As the definition of machine learning is quite ambiguous depending on the context and operating field, Gu et al. used the term "machine learning" to describe:

- A diverse collection of high-dimensional models for statistical prediction, combined with
- So-called "regularization" methods for model selection and mitigation of overfit, and
- Efficient algorithms for searching among a vast number of potential model specifications (Gu, Kelly, & Xiu, 2020)

All machine learning definitions agree on the fact that machine learning consists of a number of algorithms that learn from data and that use the acquired knowledge for automated data analysis. Large numbers of machine learning algorithms have been designed in the past years. The algorithms that were most encountered in the meta-analysis will be briefly discussed in the following subsections.

2.1 Artificial Neural Networks

Artificial Neural Networks (ANN) are inspired by the human brain. In particular the large network of neurons that forms the structure of the brain (Hahn, 2014). ANNs are constructed out of thousands of nodes that are interconnected (see Figure 1). The input nodes receive data which is fed to the neural network in which each node is connected to multiple nodes in the next layer. When input goes from one node to the next node, the data is multiplied by a certain weight. To produce the final output, the network sums the weighted data in the last layer. Initially, it is not possible to know for each node what is the right weight. The initial weights are thus randomly set. The predicted outcome is compared to actual output to optimally train the neural network. The difference between the actual output and the ANN output is used to update the weights of the nodes in the ANN (Brombin, 2017). The use of these neural networks enables the algorithm to successfully capture nonlinear relationships among variables describing complex systems (Ghaziri, Elfakhani, & Assi, 2000).

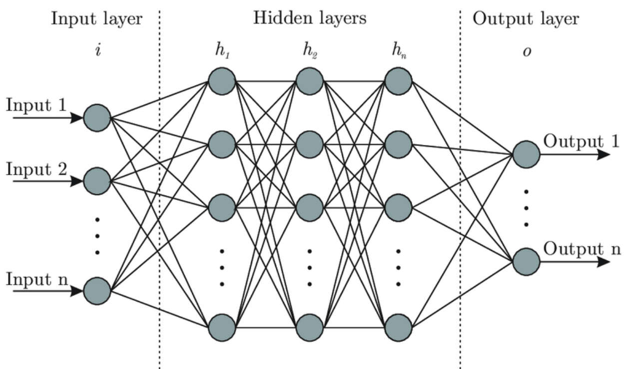

Figure 1. An example of an Artificial Neural Network

2.2 Random Forests

Random Forests (RF) are a form of machine learning that uses a collection of decision trees (see Figure 2). Decision trees are constructed of a tree-like structure that begin with one decision, the “root”, and disperse to several branches that will finally lead to a decision (Das & Behera, 2017). Multiple decision trees, each with their own probability distribution, together form a Random Forest (Maragoudakis & Serpanos, 2010). Random Forests are used for two types of tasks; classification tasks and regression tasks. RFs with classification trees are used to predict a label, which is selected by the majority voting from the decision trees. In finance, this would result in e.g. a binary decision that predicts whether the price of an asset will increase or decrease. RFs with regression trees are used to predict a quantity, which is selected by taking the mean result of the decision trees in the Random Forest (Huang, 2019). In finance, this would result in e.g. a quantified forecast of an asset’s return.

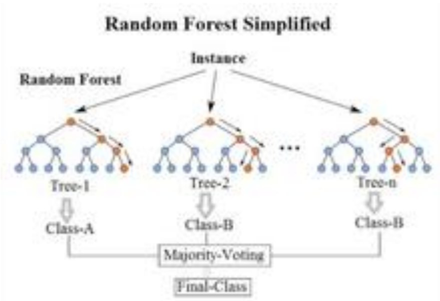

Figure 2. An example of a Random Forest

2.3 Support Vector Machines

Support Vector Machine (SVM) algorithms are also used for both classification and regressions tasks. The goal of SVM algorithms is to separate two or more sets of data into clusters by creating an optimal separating line, plane or hyperplane, called support vector classifiers (Das & Behera, 2017) (Sebastiao & Godinho, 2021). The support vector classifiers are selected with the maximum margins between the different datasets. To classify the data into separate datasets, the input data from the training sample needs to be placed into a higher dimensional space. When the input data is in a one-dimensional space, the data is squared into a two-dimensional space, so that a one-dimensional line, the hyperplane, can form the support vector classifier (see Figure 3). When the input data is in a two-dimensional space, the data is calculated into a three-dimensional space, so that a two-dimensional plane can form the support vector classifier. This process of calculating the data in a x-dimensional space into a (x + 1)-dimensional space progresses as more parameters are added. For non-linear input data, the mapping to a higher dimensional space is performed with the help of a kernel function. When the non-linear input data is mapped into a multi-dimensional space, it is possible to apply linear models to create support vector classifiers (Koranga, et al., 2021) (Sebastiao & Godinho, 2021).

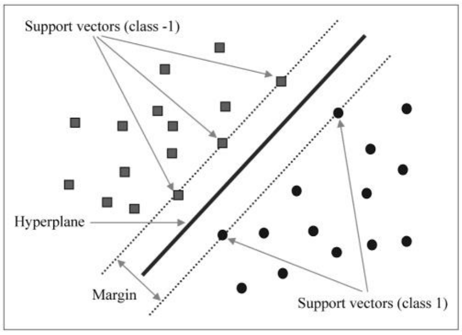

Figure 3. An example of a Support Vector classifier

3. FUNDAMENTAL INVESTMENT ANALYSIS

For many decades investors and institutions have searched for the most optimal investment analysis tools. The analysis of financial asset prediction models can be divided into the following three categories: fundamental analysis, technical analysis, and sentiment analysis (Huang, 2019). The following subsections will discuss the theory on fundamental and technical analysis of the following financial assets: stocks, options, and bonds.

3.1 Stock Pricing

Stocks are financial products that are used by companies to raise capital. When a company offers stocks for the first time, it is called an Initial Public Offering (IPO). With an IPO, an investment banking firm selects the opening price for one stock. Companies can also decide to issue additional shares when it already has shares on the market. These shares are called seasoned offerings. The offering of seasoned shares and IPOs are conducted on the primary market. The market for existing shares to be traded by investors and investment institutes is conducted on secondary markets. The owners of shares are called shareholders. Shareholders are owners of the company, have voting rights and are entitled to dividends when the company decides to pay out dividends. The percentage of dividends and votes of a shareholder depends on the percentage of shares owned (Brealy , Myers, & Marcus, 2001). There countless theories on asset pricing. In the meta-analysis, the most commonly encountered benchmarks for asset pricing were the simple buy & hold (B&H) strategy, the capital asset pricing model, and the Fama-French multi-factor models. The last two models are briefly discussed in the following subsections.

3.1.1 Capital Asset Pricing Model

Sharpe, Lintner, and Treynor introduced the CAPM in which the risk premium of an asset moves in proportion to the asset’s beta (Sharpe, 1964), (Lintner, 1965), (Treynor, 1961). The relation between the asset’s return and the asset’s beta is defined as follows:

$$E(r_i) = r_f + \beta_i(E(r_M) - r_f)$$

In the equation, $E(r_i)$ is defined as the expected return on asset i, r_f is the risk-free rate of return, β_i is the beta of the asset, and $(E(r_M) - r_f)$ is the market risk premium (Ndikum, 2020). For the risk-free rate of return, in theory, the return of a government bond is usually taken as it is considered to be the least risky investment opportunity. The beta of an asset is defined as the sensitivity of the asset in respect to the market (Brealy, Myers, & Allen, 2017). This sensitivity is characterized as follows: assets with a beta of 1.0 follow the exact movements of the market. An asset's movements with a beta of -1.0 are the exact opposite of the movements of the market. The market risk premium refers to the difference between the return of the market and the risk-free rate of return. Although the CAPM can give a proper estimation, the CAPM has several limitations. E.g. it assumes that the sole influence on an asset's return is its risk in regards with the market risk. Furthermore, Black indicated that a risk-free asset does not exist. In his adaptation on the CAPM, the zero-beta CAPM, the risk-free rate or return is replaced by a zero-beta portfolio which led to improved empirical results (Black F. , 1972). However, Fama & French indicated that the CAPM should only be used as a theoretical framework for the relationship between risk and return, as empirical problems were found in research. (Fama & French, 2004).

3.1.2 Fama-French Multi-Factor Models

Fama and French introduced multi-factor models with multiple risk factors. The multi-factor models are characterized by the fact that more risk factors are taken into account through multiple betas. In the meta-analysis, the most commonly used Fama-French multi-factor models that are used as benchmarks, are the three-factor Fama-French model and the five-factor Fama-French model (Fama & French, 1993). The equation for the three-factor Fama-French model is as follows (Brealy, Myers, & Allen, 2017), (Kohlscheen & Takáts, 2021):

$$\begin{aligned} r_i - r_f = {} & \beta_M(r_M - r_f) + \beta_{size}(SMB) \\ & + \beta_{book-to-market}(HML) + \alpha \end{aligned}$$

In the equation, r_i is defined as the return on asset, or portfolio, i, r_f is the risk-free rate of return, $(r_M - r_f)$ is defined as the market risk premium, SMB (Small Minus Big) is the return on small-firm stocks minus return on large-firm stocks, and HML (High Minus Low) is the return on high book-to-market-ratio stocks minus return on low book-to-market ratio stocks (Brealy, Myers, & Allen, 2017). The betas in this model have the same purpose as in the CAPM. The betas are the sensitivity of the performance of the underlying stock in relation with the three factors. In later research, Fama and French added two factors to create the Fama-French five-factor model. The two added factors are profitability patterns and investment patterns (Fama & French, 2015). The equation for the five-factor Fama-French model is as follows (Wang, Yu, & Zhao, 2021):

$$\begin{aligned} r_i - r_f = {} & \beta_M(r_M - r_f) + \beta_{size}(SMB) \\ & + \beta_{book-to-market}(HML) \\ & + \beta_{profitability}(RMW) \\ & + \beta_{investment}(CMA) + \alpha \end{aligned}$$

In the equation, RMW (Robust Minus Weak) is defined as the returns on stocks with robust profitability minus returns on stocks with weak profitability, and CMA (Conservatively Minus Aggressively) is defined as the returns on stocks of low investment firms minus the returns on stocks of high investment firms. Fama & French state that the five-factor Fama-French model is an improvement over the three-factor Fama-French model (Fama & French, 2015).

3.2 Option Pricing

Options are financial contracts on common stocks that are regularly traded among investors. Investors have multiple incentives to trade in options. Options are used to produce a return on the volatility of assets by speculating whether the value of the asset will increase or decrease in the future, or options can be used to hedge against risk.

There are two types of options: call options and put options. Call options give the owner of the contract the right, but not the obligation, to buy the underlying asset at a pre-determined exercise price before or on a specified maturity date. Put options give the owner of the contract the right, but not the obligation, to sell the underlying asset at a pre-determined exercise price before or on a specified maturity date. Whether the contract can be exercised on the maturity date or also before the maturity date depends on the type of contract. A European option can only be exercised on the specified maturity date and an American option can be exercised at any time till the maturity date (Brealy, Myers, & Allen, 2017). Figure 4 shows the payoff diagrams for the buyer of a call option and the buyer of a put option. The payoff of the buyer of a call increases when the value of the underlying asset exceeds the pre-determined exercise price, also called In-The-Money (ITM). The buyer of the call then has the right to buy the asset at a price below the asset's value. If the value of the underlying asset is below the exercise price when exercised, the call option is Out-Of-The-Money (OTM) and worthless. The opposite applies to the buyer of a put option. The value of the put option increases when the price of the underlying asset decreases. The buyer of the put then has the right to sell the asset above the asset's value. If the value of the underlying asset is above the exercise price when exercised, the put option is OTM and worthless.

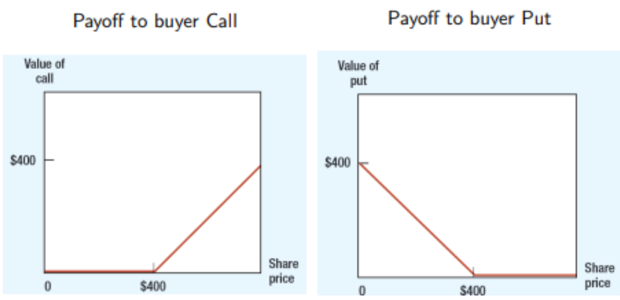

Figure 4. Call and Put Option Payoff Diagram

There are three methods to calculate the price of options before the maturity date: constructing option equivalents from common assets and borrowing, the binomial method, and the Black-Scholes method (Brealy, Myers, & Allen, 2017). The research papers on the performance of machine learning in option pricing almost exclusively used the Black-Scholes method as benchmark to compare machine learning algorithms' performance. The Black-Scholes was first introduced in 1973 to price call options and was later extended to price put options (Black & Scholes, 1973) (Ghaziri, Elfakhani, & Assi, 2000). The Black-Scholes formula, adapted by Merton to include dividends, for the calculation of the price of a call option is as follows:

$$C = Se^{-qT}N(d_1) - Ke^{-rT}N(d_2)$$

$$d_1 = \frac{\ln\left(\frac{S}{K}\right) + (r - 0.5\sigma^2)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

In the equation, S is the current asset price, K is the option strike price, T is time till maturity, q and r are the annualized dividend and risk-free rates, and σ is the annualized volatility of the underlying asset (Culkin & Sanjiv R., 2017).

3.3 Bond Pricing

Bonds are financial products that are issued by companies to raise extra cash for long-term investments. Bonds can be seen as long-term loans to companies. Not only companies issue bonds, governments and government subsidiaries, such as municipalities, also issue bonds. Companies usually turn to issuing bonds when selling additional shares or loaning from a bank seems to be sub-optimal. The bond market is mostly occupied by institutional investors, such as insurance companies, pension funds, and mutual funds. Individual Investors that are interested in investing in financial products, but deem the stock market to be too much of a risk, may choose to invest in corporate or government bonds (Bali, Goyal, Huang, Jiang, & Wen, 2020). Bonds are considered to be less risky than stocks, because owners of bonds are entitled to a fixed number of payoffs until the maturity date of the bond is reached. These payoffs consist of interest payments, called coupons, and, at maturity, the face value of the bond, also called the bond's principal. The formula for the calculation of the bond price of a bond is as follows:

$$Bond = \frac{Coupon}{(1+r)^1} + \frac{Coupon}{(1+r)^2} + \cdots + \frac{Coupon + Principal}{(1+r)^n}$$

In the equation, the coupon is the pre-determined interest payment, the principal is the face value of the bond, r is the rate of return of the bond, also called the yield to maturity, and n is the number of payoff periods. (Brealy, Myers, & Allen, 2017).

4. METHODOLOGY

The scientific procedure to test the hypotheses is through a meta-analysis. A meta-analysis is an analysis that combines the results of multiple scientific research papers. Through the meta-analysis it can be analysed whether machine learning is associated with higher forecasting performance in financial asset pricing over a large number of different research samples. When the results of the meta-analysis lead to the acceptation of the three hypotheses, it can be confirmed that machine learning algorithms outperform fundamental investment analysis. The library of the University of Twente gives access to databases like Scopus, Google Scholar, IEEE Xplore Digital Library, Oxford Journals, SpringerLink, and Journal Citation Reports that will be utilized to find relevant research papers from journals such as the Journal of Forecasting, the Journal of Business, the Journal of Asset Management, the Journal of Financial Economics, etc. The results will be documented and presented in three tables corresponding to their financial asset class. The implementation of machine learning in each of the asset classes will be assessed through the categories performance, risk, and growth, as these are common used variables in traditional asset price forecasting. With the results displayed, conclusions can be made and the three hypotheses can be either accepted or rejected.

5. MACHINE LEARNING IN FUNDAMENTAL INVESTMENT ANALYSIS

5.1 Machine Learning for Stock Pricing

The stock market is still the most active financial asset market for investors worldwide. Fundamental analysis for many years has been the most important tool for the prediction of movements of individual stocks and stock markets. In the last two decades, there has been a significant number of research on the implementation of machine learning in stock pricing. The meta-analysis mostly focused on researches that assessed the performance of machine learning algorithms against the performance of benchmark models such as the CAPM, the Fama-French multi-factor models, and the buy & hold strategy. The meta-analysis regarding machine learning for stock pricing consists of 32 research papers. The assessment of the meta-analysis will be done through the three sub-categories performance, risk, and growth.

5.1.1 Performance

The performances of the stock pricing tools and the machine learning algorithms are the methods' ability to closely predict the movements or the price of the underlying stock. The use of machine learning algorithms for predicting the movements of a stock is called classification. With classification, the sole purpose of the prediction models is to predict whether the price will increase or decrease. The use of machine learning algorithms for predicting the price of a stock is called regression. With regression, the purpose is to predict a numerical value. To compare the performances of machine learning methods and fundamental analysis tools, the literature regarding classification methods and the literature regarding regression methods will be separated as they often have different manners of comparison.

The literature in the meta-analysis uses the classification method for portfolio selection. In machine learning, the classification method is used to select stocks that will increase in value in the future. These stocks are then put together in a portfolio. So, the comparison of the performance of machine learning algorithms versus the performance of fundamental analysis is conducted by looking at the returns of the overall portfolios. The method that creates the largest return for investors is seen as the best performer. The same goes for comparison made with the simple buy & hold strategy. The buy & hold strategy is a passive strategy where investors buy stocks for their portfolio and hold them for a long period. The buy & hold method is often seen as a benchmark in the meta-analysis. The meta-analysis shows that machine learning algorithms are superior to the buy & hold strategy. The literature in the research sample shows that machine learning performs better in creating higher returns, e.g. Aguirre et al. showed that the machine learning method beats the buy & hold strategy by 4% (Aguirre, Medina, & Méndez, 2020). Next to the buy & hold strategy, machine learning algorithms outperform other benchmark models. In the literature in the research sample, all articles conclude that machine learning algorithms are the superior performer for portfolio selection. E.g. Adosoglou et al. use machine learning powered sentiment analysis to capture semantics in 10-Ks, annual reports on companies' financial information, for enhanced portfolio selection which increased the yearly risk-adjusted abnormal return with 10% (Adosoglou, Lombardo, & Pardalos, 2021), and Choi & Renelle proposed a machine learning model built on deep learning techniques and recurrent neural networks which topped the best performing conventional portfolio's annual yield with 2,56% (Choi & Renelle , 2019). Further examples of the superior performance of machine learning algorithms over fundamental analysis can be found in table 1, and appendix 6.A.

The regression method is used to predict future stock prices. In the meta-analysis, multiple methods of comparison were encountered. E.g. for the comparison between fundamental analysis and machine learning algorithms, Ndikum used the Mean Squared Error (MSE) to measure performances. The MSE is the mean of the squared differences between predicted values and observed values. The MSE demonstrates the superior performance of the machine learning models as all proposed machine learning methods outperformed the CAPM by at least 1.2373 in MSE (Ndikum, 2020). Overall, the meta-analysis showed that in all articles machine learning methods outperformed fundamental analysis. E.g. Barboza et al. showed that machine learning models show 10% more pricing accuracy than benchmark models, with Random Forest as the best performer (87%) (Barboza , Kimura, & Altman, 2017), and Saini & Sharma state that the LSTM Neural Network produces the highest accuracy (87.86%) as compared to benchmark machine learning methods (Saini & Sharma, 2019). Further results of the meta-analysis can be found in table 1, and appendix 6.A.

5.1.2 Risk

In the assessment of the use of machine learning algorithms in stock pricing, we have to take risk into account. Multiple research papers in the research sample used the Sharpe ratio as one of the measurements for performance. The Sharpe ratio is the ratio of the risk premium to the standard deviation:

$$Sharpe\ ratio = \frac{Risk\ Premium}{Standard\ Deviation} = \frac{r - r_f}{\sigma}$$

Sharpe ratios are used to quantify the risk-adjusted performance of portfolios and stocks (Brealy , Myers, & Marcus, 2001). The meta-analysis showed that machine learning algorithms often outperformed benchmark models in terms of the Sharpe ratio. E.g. Kaczmarek & Perez showed that the random forest outperformed the benchmark models by 16.5% in terms of the Sharpe ratio (Kaczmarek & Perez, 2021), and Geertsema & Lu state that the proposed method is capable of producing a higher Sharpe ratio (0.51) than the CAPM (0.016), and the Fama & French multifactor models (0.040 & 0.101) (Geertsema & Lu, 2020).

Next to higher Sharpe ratios, machine learning algorithms have the advantage of taking behavioural finance out of the equation. Behavioural finance is defined as the area of finance dealing with the implications of reasoning errors on financial decisions (Hillier, Clacher, Ross, Westerfield, & Jordan, 2017). Hillier et al. describe three main categories of such errors, namely biases, framing effects, when investors' decisions depend on how problem are framed, and heuristics, which are shortcuts or rules of thumb to make decisions. These cognitive errors can cause mispricing of certain stocks. The risk of cognitive errors is nullified in machine learning as machine learning algorithms act solely on past training data.

5.1.3 Growth

The stock market is largely correlated with economic growth. Although the literature in the research sample most likely include multiple macroeconomic variables, including economic growth, it is not explicitly mentioned in the literature. Geertsema & Lu mention the inclusion of an expected asset growth factor in the training data which improved the pricing performance of the machine learning model (Geertsema & Lu, 2020). This, however, does not help conclude that the inclusion of economic growth as a macroeconomic variable in training data is a prerequisite.

5.1.4 Results

The meta-analysis showed that all articles in the research sample agreed on the superior performance of machine learning algorithms over fundamental investment analysis. Next to comparisons with the buy & hold strategy, the CAPM, and the Fama-French multifactor models, literature often compares their proposed methods with other machine learning models. E.g. Jan & Ayub (Jan & Ayub, 2019) created a model based on the Fama-French five-factor model that outperformed benchmark machine learning models. Table 1 shows a summarized version of the results table. In the table, ten articles from the meta-analysis are given with their corresponding conclusions regarding the three sub-categories performance, risk, and growth. The full results table can be found in the appendix, under appendix 6.A. The results state that the sample of 32 research papers state that machine learning methods improve pricing performance with roughly 40%. Furthermore, the Sharpe ratio is improved by 201.33% through the use of machine learning methods, mainly because of the outlier of Geertsema & Lu's research. Excluding Geertsema & Lu's results still leads to an increase in Sharpe ratios of 33.03%. These results help conclude that hypothesis 1 can be accepted, and thus that machine learning algorithms are associated with higher pricing accuracy than traditional stock pricing methods.

Table 1. Results table of the meta-analysis on the application of machine learning in stock pricing of 10 research papers

ARTICLE	SAMPLE	PERFORMANCE	RISK	GROWTH
(Adosoglou, Lombardo, & Pardalos, 2021)	All available SEC 10-K filings – 1998-2018	The ML strategy increases yearly risk-adjusted abnormal return with 10%	Very small portfolio betas suggest lower risk	The strategy avoids high beta, high growth stocks
(Aguirre, Medina, & Méndez, 2020)	Historical prices of variable income asset representative of the Nasdaq Stock index 2013-2019	The ML method beat the B&H strategy by 4%	X	X
(Barboza , Kimura, & Altman, 2017)	North American firms 1985-2013	ML models show 10% more accuracy, with RF as best performer (87%)	ML could be an important tool to aid credit risk analysis	X
(Choi & Renelle , 2019)	Russell 1000 Index 1996-2017	The ML model improves	The ML model improves Sharpe	X

		returns by 2.56%	ratio by 1.93%	
(Drobetz & Otto, 2020)	All firms publicly listed in Eurozone countries 1990-2020	ANN outperforms benchmark models by at least 52.48%	ANN produces the highest Sharpe ratio (1.41 vs 1.24)	X
(Geertsema & Lu, 2020)	US common equities traded on NYSE, Amex, or Nasdaq Jul, 1963-Dec, 2019	X	The ML method produces a higher Sharpe ratio (0.51) than the CAPM (0.016), and FF models (0.040 & 0.101)	The expected growth factor is a prominent factor that improves pricing performance
(Kaczmarek & Perez, 2021)	S&P 500 stocks Dec 31, 1999-Dec31, 2019	X	The proposed model outperforms the Sharpe ratio of the benchmark model by 16.5%	X
(Lee & Tzeng, 2013)		The proposed model can improve accurate prediction rates to 74.3% or 83.1%	X	X
(Maragoudakis & Serpanos, 2010)	Greek stock securities Nov, 2007-Jan, 2010	The proposed method outperformed the B&H strategy by 12.5% to 26% in the first two weeks and 16% to 48% in the remaining weeks	X	X
(Wen, Yang, Song, & Jia, 2009)	50 S&P 500 stocks Jun 15, 2005-Jun 11, 2007	The SVM method outperforms the B&H strategy in profit by 21.46%	X	X
RESULTS	32 Research Papers	ML methods improve pricing with ±40%	ML improve the Sharpe ratio with ±201.33%	Addition of expected growth factor improves pricing performance

5.2 Machine Learning for Option Pricing

Th most important finding in the field of option pricing was the Black-Scholes method introduced in 1973. There has been a lot of further research on the Black-Scholes method to optimize the model and make useful adaptations, e.g. the adapted equation by Merton to include dividends. The literature in the meta-analysis focused on the comparison between the machine learning algorithms and the Black-Scholes method. The meta-analysis regarding machine learning for option pricing consists of 23 research papers. The assessment of the literature review will be done through the three sub-categories performance, risk, and growth.

5.2.1 Performance

The literature was almost unanimous in selecting machine learning algorithms as the better performer over the Black-Scholes method. In three papers, there were conditions where machine learning was not the superior pricing method. Kitamura & Ebisuda state in their research paper that the performance of an ANN in pricing American-style call option was poor. However, they stated that this could be the result of a small research sample and the use of only two input nodes to the ANN (Kitamura & Ebisuda, 1998). Furthermore, Benell & Sutcliffe stated that the ANN was clearly superior to the Black-Scholes method for out-of-the-money options, but, for in-the-money options, the superiority depends on the restriction of the sample space. The Black-Scholes was initially the better performer over the ANN, because the ANN had difficulties with pricing options that are deep in-the-money and with long expiry dates. The exclusion of these options led to more comparable results between the ANN and the Black-Scholes method (Benell & Sutcliffe, 2004). Finally, Malliaris & Salchenberger state that the ANN outperformed the Black-Scholes method in about half the cases (Malliaris & Salchenberger, 1993).

The remainder of the literature in the meta-analysis clearly confirm the superiority of machine learning algorithms over the Black-Scholes method. E.g. Das & Padhy state that the machine learning models significantly outperform the Black-Scholes model as well as other parametric models. The proposed ML SVR-HH hybrid improved the RMSE of the Black-Scholes method in all four datasets with 83.66%, 78.02%, 91.86%, and 87.7% respectively (Das & Padhy , 2017). Ivaşcu tested multiple machine learning methods against the performance of the Black-Scholes method. In seven non-overlapping periods, the parametric and non-parametric models were trained and tested. The machine learning algorithms offered smaller pricing errors in all periods, with the XGB boost, an additive boosting model, as the best performer with a mean pricing error of 0.803 versus a mean pricing error of 1.654 by the Black-Scholes method (Ivaşcu, 2021). Further results of the meta-analysis can be found in table 2, and appendix 6.B.

As stated earlier, three of the research papers initially stated that machine learning algorithms were not in all cases superior. However, first, Kitamura & Ebisuda state that this result can be the result of a small research sample, and the use of only two input nodes for the ANN. Second, Bennell & Sutcliffe state that, for in-the-money options, the ANN only becomes comparable with the Black-Scholes method through the exclusion of a number of options, and as this number of options is only 3.4% of the volume of the sample, it is finally concluded that the ANN approach is generally superior to the Black-Scholes method (Benell & Sutcliffe, 2004). Third, Mailliaris & Salchenberger state that the ANN outperforms the Black-Scholes method in about half of the case. This was, however in 1993 when research on ANN applications for option pricing was only just beginning (Malliaris & Salchenberger, 1993).

5.2.2 Risk

Options are crucial in hedging against risk. Through financial engineering, an investor can hedge against risk by combining financial assets. E.g. an investor can create downside protection for a stock by buying the stock for price x and buying a put option on that same stock to sell it for price x. When the stock drops below price x, an investor has the right to sell the stock for x creating downside protection. The payoff of this strategy is identical to the strategy of buying a call and investing the PV of the exercise price in a safe asset. This relationship is called the put-call parity and only holds for European options (Brealy, Myers, & Allen, 2017). For the strategy of creating downside protection to work, an investor needs to be certain of the fact that the market price of the option is equal to the actual value of the option. Option pricing is thus a very important part of portfolio hedging. As stated in the performance section, machine learning algorithms clearly outperform the Black-Scholes method. Thus, it can be said that the use of machine learning algorithms for hedging strategies is recommended over the Black-Scholes method.

Next to this, the implementation of machine learning algorithms for delta-hedging is often discussed in the literature. Das & Padhy state that the idea behind delta-hedging is to hold an option and the underlying asset in such a ratio, such that changes in the option price are well-adjusted by the underlying stock's price changes and that these changes should offset each other (Das & Padhy , 2017). So, for example, for a delta-hedge of 0.5, if a stock's price rises with $10, the price of a call option on the underlying stock should increase with $5. In table 2, it can be seen that multiple research paper indicated that machine learning algorithms deliver smaller delta-hedging errors. E.g. Gençay & Qi found that the ANNs outperform the Black-Scholes method's heding performance by 40-70%.

5.2.3 Growth

Although there is an obvious link between economic growth and market conditions, and financial options, the literature in the literature review does not focus on this link. So, unfortunately, the sub-category economic growth cannot help us accept or reject the hypothesis.

5.2.4 Results

The meta-analysis was conducted on a research sample of 23 papers. Most papers stated that the proposed machine learning algorithms outperformed benchmark models, like the Black-Scholes method and other machine learning algorithms, in performance as well as risk. Three research papers did not agree with this premise. Kitamura & Ebisuda, Benell & Sutcliffe, and Malliaris & Salchenberger concluded that machine learning was not superior in all cases. Table 2 shows a portion of the results table. In the table, some of the articles from the meta-analysis are given with their corresponding conclusions regarding the three sub-categories performance, risk, and growth. The full results table can be found in the appendix, under appendix 6.B. The results show that the machine learning methods outperformed benchmark models, such as the Black-Scholes method. Research papers used different metrics to assess the performances. Machine learning methods outperformed benchmark models in RMSE, MAD, MSPE, and mean differences. Also, the hedging performance of machine learning methods is superior to the Black-Scholes method with 30-40%. So, it can be concluded that machine learning algorithms also outperform the Black-Scholes method in terms of hedging. These results help to accept hypothesis 2, and thus confirm that machine learning algorithms are associated with higher pricing accuracy than traditional option pricing methods.

Table 2. Results table of the meta-analysis on the application of machine learning in option pricing of 10 research papers

ARTICLE	SAMPLE	PERFORMANCE	RISK	GROWTH
(Amilon, 2003)	Swedish stock index call options; 50 best performing stocks 1997-1999	ANN models outperform the BS model: ΔRMSE = 3.08 (bid) ΔRMSE = 2.16 (ask)	ANN models obtain a positive result with delta-hedging: P = €2096 (ML) P = €-5019 (BS)	X
(Benell & Sutcliffe, 2004) ANN	FTSE 100 index EU style call options 1999	OTM: ΔMAD = 10.0 ITM: ΔMAD = -7.3 (with data exclusion)	X	X
(Das & Padhy , 2017)	EU style option on the CNX BANK index 2013-2014	SVR-HH hybrid: RMSE improved by 83.66% , 78.02%, 91.86%, and 87.7% compared to BS	SVR-HH hybrid: Improved delta-hedging error by 21,36% and 8.69%	X
(Garcia & Gençay, 2000)	S&P 500 Index EU options 1987-1994	Over all years except 1987 the BS MSPE is 3 to 10 times larger than the ANNs	NNs are better for hedging than BS as the ratio is as low as 67% in 1991	X
(Gaspar, Lopes, & Sequeira, 2020)	37,952 American Put options Dec, 2018–Mar, 2019	The best performing ANN model outperformed other models in having a RMSE 40% lower than other models	X	X
(Gençay & Qi, 2001)	S&P 500 Index call option Jan, 1988–Dec, 1993	The mean of the ratio between the MSPE of the NN and BR are 0.9216, 1.0089, 1.0072, 0.9527, 1.0109, and 1.0653	ANNs outperform BS's hedging performance by 40-70 percent	X
(Ivașcu, 2021)	EU options on WTI crude oil future contracts 2017-2018	Additive boosting models: Mean pricing error = 0.803 BS: Mean pricing error = 1.654	X	X
(Kitamura & Ebisuda, 1998)		The performance of an ANN in pricing American-style call options was poor.	X	X
(Malliaris & Salchenberger, 1993)	Option-price transactions data published in the Wall Street Journal Jan 1–Jun 30, 1990	OTM: Mean difference BS = 0.506, mean difference NN = -0.118 ITM: Mean difference BS = -0.102, mean difference NN = -0.499	X	X

(Phani, Chandra, & Raghav, 2011)	American option price for companies belonging to various sectors	The NN and the SVR out performed BS by 12.42 and 15.02 in terms of MAE	X	X
RESULTS	23 Research Papers	ΔRMSE ≈ 65% ΔMAD ≈ 13.58 ΔMSPE ≈ 5-10%	ML's hedging performance is superior to the BS model ±30-40%	X

5.3 Machine Learning for Bond Pricing

There has been an abundancy of research on the application of machine learning algorithms in stock pricing and option pricing. The opposite is true for the application of machine learning algorithms in bond pricing. The literature research resulted in a literature sample of seven papers on the subject. The reason behind this relatively small number is to be debated over. A possible explanation could be that investors do not see much value in bonds as they are seen as predictable assets with very low risk. The available literature will be assessed through the three sub-categories performance, risk, and growth.

5.3.1 Performance

The meta-analysis shows that in the literature review, the use of machine learning algorithms was beneficial for the predictability of bond returns. Bianchi et al. state that machine learning methods provide strong statistical evidence in favour of bond return predictability and that this is largely due to the ANNs' ability of capturing nonlinearities in the data (Bianchi, Büchner, & Tamoni, 2021). Shen & Wang use SVMs in valuing corporate bonds and show that it is beneficial to integrate the SVMs in combination with the copula function to analyse the value of corporate bonds, because the proposed SVM model increases pricing accuracy and hedging effectiveness compared to traditional models, such as Ordinary Least Squares (OLS) and the Black-Scholes model (Shen & Wang, 2011). Further results in performance of machine learning algorithms can be seen in table 3, and appendix 6.C.

5.3.2 Risk

In previous sections, it is stated that for the risk-free rate, in equations such as the CAPM, the multi-factor Fama-French models, and the Black-Scholes method, the return of a government bond is usually taken. Government bonds are used in these equations for the risk-free rate, because government bonds have very little risk of default. Corporate bonds, however, definitely do have default risk. So, it is important that this risk is taken into account when pricing bonds. Götze et al. link the availability of risk assessment to the good performance of the machine learning methods. Especially for catastrophe (CAT) bonds, risk assessment is very important as CAT bonds are issued by insurance companies to transfer risk to investors and companies in case of natural catastrophes (Götze, Gürtler, & Witowski, 2020). Also, in Guo et al. it is stated that the plausible source for the predictive power of the yield signal, that is integrated with machine learning algorithms, is its ability to predict changes in fundamentals that influence bond default risk (Guo, Lin, Wu, & Zhou, 2021).

5.3.3 Growth

Together with banking and stock markets, the market for government bonds is positively related to economic growth. The effect of corporate bonds on economic growth is correlated with the expansion in size of the market for government bonds (Thumrongvit, Kim, & Pyun, 2013). The value of bonds has a great influence on economic growth and vice versa. Bianchi et al. agrees with this premise as they found a strongly positive coefficient of excess bond returns on uncertainty about economic growth (Bianchi, Büchner, & Tamoni, 2021). Guo et al. found that a trading strategy based on the yield trend signals earns higher returns in slow economic growth and recession (Guo, Lin, Wu, & Zhou, 2021). So, due to the correlation between the bond market and economic growth, economic growth is an important economic variable to take in account when applying machine learning algorithms in bond pricing.

5.3.4 Results

The meta-analysis on the application of machine learning algorithms in bond pricing has shown that there has been little research on the subject. The literature in the small research sample, however, was positive about the implementation of machine learning. The table below shows the results of the meta-analysis. Increased returns and reduced RMSEs show that machine learning methods are beneficial in bond pricing. Next to that, machine learning's ability to assess and predict risk helps improve the forecasting performance. Finally, Bianchi et al. state that the coefficient between returns and uncertainty about growth shows that the link between machine learning and growth. The research papers overall showed that pricing performance is improved by the implementation of machine learning methods, and thus we can conclude that hypothesis 3, machine learning algorithms are associated with higher pricing accuracy than traditional bond pricing methods.

Table 3. Results table of the meta-analysis on the application of machine learning algorithms in bond pricing

ARTICLE	SAMPLE	PERFORMANCE	RISK	GROWTH
(Bianchi, Büchner, & Tamoni, 2021)	U.S. Treasury Bills	Machine learning methods provide strong statistical evidence in factor of bond return predictability	X	A strongly positive coefficient of excess bond returns on uncertainty about economic growth was found
(Ganguli & Dunnmon, 2017)	762,678 bonds	ANNs and GLMs give the best results in terms of combined accuracy and speed	X	X
(Götze, Gürtler, & Witowski, 2020)	597 CAT bonds Jan, 2002-Dec, 2017	RF yields a considerably lower mean RMSE of 0.0087 than other models	The availability of risk assessment is among the potential causes for the good performance of linear regression models	X
(Guo, Lin, Wu, &	LBFI database on	It is more informationally efficient and	The plausible source for	The trading strategy

Zhou, 2021)	corporate bonds Jan, 1973-Mar, 1998	capable of detecting a strong return predictability in the corporate bond market	the predictive power of the yield signal is its ability to predict changes in fundamentals that influence bond default risk	based on yield trend signals earns higher returns in periods of slow economic growth and recession
(He, Feng, Wang, & Wu, 2021)	19,782 unique bonds for public & private companies 1976-2017	The RF forecasts delivers a monthly return of 1.48% over a five-factor model	X	X
(Kratsios & Hyndman, 2020)	German bond data for 31 maturities Jan 4, 2010-Dec 30, 2014	The ML model outperforms the rest by progressively larger margins: 2.749 x 10^{-24} vs 2.360 x 10^{-4}	`x	X
(Shen & Wang, 2011)	Xin-gang stock Sep 8, 2008-Dec 31, 2010	It is a beneficial attempt to integrate SVM and copula function to analyse the value of convertible bonds	X	X
RESULTS	7 Research Papers	Increased returns and reduced RMSEs show that ML methods are beneficial in bond pricing	ML method's ability to assess and predict risk improves the forecasting performance	The coefficient between returns and uncertainty about growth shows the link between ML and growth

6. CONCLUSIONS

The meta-analysis consisted of a review of 63 research papers; 32 papers on the subject of machine learning in stock pricing, 23 papers on the subject of machine learning in option pricing, and 7 papers on the subject of machine learning in bond pricing. An additional 32 research papers assisted in constructing a theoretical framework for the concepts of machine learning, stock pricing, option pricing, and bond pricing.

The 32 research papers on machine learning in stock pricing used differing benchmark models to test the performance of machine learning algorithms. Benchmark models such as the CAPM, the Fama-French multifactor models, the buy & hold strategy, and machine learning models were in all cases outperformed by the proposed models in producing more accurate returns, and higher Sharpe ratios. Machine learning algorithms improved pricing performance by ± 40% and improved Sharpe ratios by ± 200%. The high increase in Sharpe ratio is due to the outlier results of the research of Geertsema & Lu. Excluding these results still leads to an increase in Sharpe ratio of 33.03%. The results led to accepting hypothesis 1.

For option pricing, all but three of the papers on machine learning in option pricing agreed that machine learning is associated with higher pricing performance. Most papers stated that the proposed machine learning algorithms significantly outperformed benchmark models the Black-Scholes model and other machine learning models in RMSE, MAD, MSPE, and mean differences. Furthermore, the proposed machine learning algorithms produced roughly 30-40% smaller delta-hedging errors. Three of the research papers concluded that the Black-Scholes method was not outperformed by machine learning in all cases. However, these conclusions can be refuted as Kitamura & Ebisuda had a small research sample and only two input nodes for the ANN (Kitamura & Ebisuda, 1998), Benell & Sutcliffe in the end concluded that ANN was superior after excluding some of the data (Benell & Sutcliffe, 2004), and Malliaris & Sutcliffe stated that the research phase was in its early beginnings and that the application of machine learning in option pricing showed a lot of potential (Malliaris & Salchenberger, 1993).

For machine learning in bond pricing, a smaller number of relevant papers was available. The research papers stated that increased returns and reduced pricing errors showed that machine learning methods could be beneficial in bond pricing. The pricing performance of machine learning methods is improved by it's ability to assess and predict risk. Next to that, the literature stated that there is a correlation between growth and bond pricing that needs to be taken into account. These results led to the acceptation of hypothesis 3.

To conclude, the meta-analysis consisted of 63 research papers on previous research on machine learning algorithms applied in financial asset pricing. Through the combination of the results of previous research, hypotheses 1, 2, and 3 could be accepted. With these three sub-hypotheses accepted, the main hypothesis "machine learning algorithms outperform fundamental investment analysis" is also accepted.

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8. APPENDIX

6.A Full results table of meta-analysis on the application of machine learning in stock pricing

ARTICLE	SAMPLE	PERFORMANCE	RISK	GROWTH
(Adosoglou, Lombardo, & Pardalos, 2021)	All available SEC 10-K filings – 1998-2018	The ML strategy increases yearly risk-adjusted abnormal return with 10%	Very small portfolio betas suggest lower risk	The strategy avoids high beta, high growth stocks
(Aguirre, Medina, & Méndez, 2020)	Historical prices of variable income asset representative of the Nasdaq Stock index 2013-2019	The ML method beat the B&H strategy by 4%	X	X
(Ahmed, Ghoneim, & Saleh, 2020)	Historical data of Egyptian and Nasdaq stock market	The ML model showed a significant improvement, in some cases more than 60%	X	X
(Bao, Lu, & Zhang, 2004)	Closing prices of Haier of Shanghai stock exchange Apr 15, 2003-Nov 25, 2003	SVM provides a promising alternative for financial forecasting	X	X
(Barboza , Kimura, & Altman, 2017)	North American firms 1985-2013	ML models show 10% more accuracy, with RF as best performer (87%)	ML could be an important tool to aid credit risk analysis	X
(Chen, Pelger, & Zhu, 2020)	All securities on CRSP 1967-2016	The proposed model outperforms benchmark models	The proposed method produced a Sharpe ratio twice as high than benchmark models	X
(Choi & Renelle , 2019)	Russell 1000 Index 1996-2017	The ML model improves returns by 2.56%	The ML model improves Sharpe ratio by 1.93%	X
(Drobetz & Otto, 2020)	All firms publicly listed in Eurozone countries 1990-2020	ANN outperforms benchmark models by at least 52.48%	ANN produces the highest Sharpe ratio (1.41 vs 1.24)	X
(Geertsema & Lu, 2020)	US common equities traded on NYSE, Amex, or Nasdaq Jul, 1963-Dec, 2019	X	The ML method produces a higher Sharpe ratio (0.51) than the CAPM (0.016), and FF models (0.040 & 0.101)	The expected growth factor is a prominent factor that improves pricing performance
(Gu, Kelly, & Xiu, 2020)	All firms listed in the NYSE, AMEX, and Nasdaq Mar, 1957-Dec, 2017	ANN are the best performing method in asset pricing	The ANN produces higher Sharpe ratios than benchmark strategies	X
(Houlihan & Creamer, 2021)	Asset price data from CRSP & 4.1 million messages from StockTwits Jul 13, 2009-Oct, 31 2012	Message volume and sentiment can be used to predict asset price directional moves	Message volume and sentiment can be used as a risk factor in an asset pricing model framework	X
(Huang, Machine Learning for Stock Prediction on Fundamental Analysis, 2019)	S&P 500 stocks 1995-2017	RF achieves the best performance with portfolio scores of 0.414 and -0.305	X	X
(Jan & Ayub, 2019)	Pakistan Stock Exchange 2000-2015	The best performing ANN had a success rate of accurate prediction of 98%	X	X
(Kaczmarek & Perez, 2021)	S&P 500 stocks Dec 31, 1999-Dec31, 2019	X	The proposed model outperforms the Sharpe ratio of the benchmark model by 16.5%	X
(Kamalov, 2020)	Stock prices of Coca-Cola, Cisco systems, Nike, and Goldman Sachs 2009-2019	ANN models outperform other models in predicting significant changes	X	X
(Kamble, 2017)	Various stocks listed in NSE & BSE	The ML model improves accuracy of short-term trend prediction	The random forest model yields a good result with less risk	X
(Kantavat & Kijsirikul, 2008)	SET 50 2002-2007	The B&H method is outperformed in bear markets with 1-5%	X	X
(Lee & Tzeng, 2013)		The proposed model can improve accurate prediction rates to 74.3% or 83.1%	X	X
(Li, Deng, & Luo, 2009)	Stock quote time series of TESCO PLC and the DJIA	The rate of return improved by 5.26% and 2.3 compared to the B&H strategy	X	X
(Li & Mei, 2020)	SSE 50 and CSI 300 index Jan, 2012-Dec, 2017	ANN with 2 hidden layers performs best	X	X
(Maragoudakis & Serpanos, 2010)	Greek stock securities Nov, 2007-Jan, 2010	The proposed method outperformed the B&H strategy by 12.5% to 26% in the first two weeks and 16% to 48% in the remaining weeks	X	X
(Ndikum, 2020)	All publicly traded US stocks available on the WRDS (782 stocks) 1983-2019	All ML methods outperformed CAPM in MSE by at least 1.2373	Literature explores how ML can be used to directly forecast macroeconomic variables to identify	X

			systematic risk and economic recessions	
(Pang, Zhou, Wang, Lin, & Chang, 2020)	Single stock data on the Shanghai A-share market Jan 1, 2006-Oct 19, 2016	The proposed model's accuracy is 10% higher than benchmark models	X	X
(Rasekhschaffe & Jones, 2019)	5,907 stocks per month in 22 developed markets 1994-2016	The ML model outperforms FF in producing a higher alpha 1.90 vs 1.13 (US) and 1.50 vs 0.95 (ROW)	X	X
(Ul Haq, Zeb, Lei, & Zhang, 2021)	88 Nasdaq listed stocks Jan 1, 2014-Jan 1, 2016	ML approaches produce promising results with an accuracy of 59.44% for the best performer (56% is satisfying for binary stock predicition)	X	X
(Saini & Sharma, 2019)		LSTM NN produces the highest accuracy (87.86%) as compared to other ML methods	X	X
(Teng, Li, & Chang, 2020)	All firms listed in the NYSE, AMEX, and Nasdaq Mar, 1957-Dec, 2016	ML methods can help improve empirical understanding of asset prices. NNs are the best performing methods	ML methods can create portfolios with higher Sharpe ratios	X
(Wen, Yang, Song, & Jia, 2009)	50 S&P 500 stocks Jun 15, 2005-Jun 11, 2007	The SVM method outperforms the B&H strategy in profit by 21.46%	X	X
(Zhang & Maringer, 2014)	S&P 500 stocks Jan 1, 2009-Dec 3, 2012		The ML method outperformed benchmark models in producing a higher Sharpe ratio	X
(Zhao, 2019)	X	In stably increasing markets, the buy/hold strategy is optimal. A ML strategy is expected to help	Evaluating the risk through the proposed ML methods provides guidance for quantitative trading	X
(Zhong & Enke, 2019)	SPDR S&P 500 ETF Jun 1, 2003-May 31, 2013	NNs give significantly higher classification accuracy than other ML algorithms	X	X
(Zhu, Basu, Jarrow, & Wells, 2020)	All ETFs available in CRSP database Jan, 2014-Dec, 2016	The created algorithms have a significantly higher prediction power than the FF 5 factor model	X	X
RESULTS	32 Research Papers	ML methods improve pricing with ±40%	ML improve the Sharpe ratio with ±201.33%	Addition of expected growth factor improves pricing performance

6.B Full results table of the meta-analysis on the application of machine learning in option pricing

ARTICLE	SAMPLE	PERFORMANCE	RISK	GROWTH
(Amilon, 2003)	Swedish stock index call options; 50 best performing stocks - 1997-1999	ANN models outperform the BS model: ΔRMSE = 3.08 (bid) ΔRMSE = 2.16 (ask)	ANN models obtain a positive result with delta-hedging: P = €2096 (ML) P = €-5019 (BS)	X
(Benell & Sutcliffe, 2004) ANN	FTSE 100 index EU style call options – 1999	OTM: ΔMAD = 10.0 ITM: ΔMAD = -7.3 (with data exclusion)	X	X
(Chen, et al., 2021)	European options	Laguerre NN: MSE = 1.16 x 10^{-11}	X	X
(Chowdhury, Mahdy, Alam, Al Quaderi, & Rahman, 2020)	11 Companies with differing training and testing periods	Ensemble method (DT & NN): RMSE = 1.168	X	X
(Culkin & Sanjiv R., 2017)	Simulation of 300,000 option prices	ANN based on BS: RMSE = 0.0112	X	X
(Das & Padhy , 2017)	EU style option on the CNX BANK index – 2013-2014	SVR-HH hybrid: RMSE improved by 83.66% , 78.02%, 91.86%, and 87.7% compared to BS	SVR-HH hybrid: Improved delta-hedging error by 21,36% and 8.69%	X
(Gan, Wang, & Yang, 2019)	Computer generated prices of Asian options	ML model can predict prices with high accuracy: MSE = ± 1.0 x 10^{-5}	Prediction of Asian options due to relatively lower risk	X
(Garcia & Gençay, 2000)	S&P 500 Index EU options – 1987-1994	Over all years except 1987 the BS MSPE is 3 to 10 times larger than the ANNs	NNs are better for hedging than BS as the ratio is as low as 67% in 1991	X
(Gaspar, Lopes, & Sequeira, 2020)	37,952 American Put options – Dec, 2018 – Mar, 2019	The best performing ANN model outperformed other models in having a RMSE 40% lower than other models	X	X

(Gençay & Salih, 2003)	S&P 500 Index options – Jan, 1988 – Oct, 1993	ANNs improved compared to MSPEs of BS 40-80 percent across years	X	X
(Gençay & Qi, Pricing and Hedging Derivative Securities with Neural Networks: Bayesian Regularization, Early Stopping, and Bagging, 2001)	S&P 500 Index call option – Jan, 1988 – Dec, 1993	The mean of the ratio between the MSPE of the NN and BS are 0.9216, 1.0089, 1.0072, 0.9527, 1.0109, and 1.0653	ANNs outperforms BS's hedging performance by 40-70 percent	X
(Ghaziri, Elfakhani, & Assi, Neural Networks Approach to Pricing Option, 2000)	S&P 500 index call options: 70 ITM, ATM, and OTM options – Feb 26, 1997 – Feb 27, 1997	ANN outperforms BS: ΔRMSE = 1.8068	X	X
(Hutchinson, Lo, & Poggio, 1994)	S&P 500 futures options – 1987 – 1991	All three ML methods outperform the BS model	The ANN showed a superior performance in delta-hedging	X
(Ivașcu, 2021)	EU options on WTI crude oil future contracts – 2017-2018	Additive boosting models: Mean pricing error = 0.803 BS: Mean pricing error = 1.654	X	X
(Jang, Yoon, Kim, Gu, & Kim, 2021)	S&P 500 EU call options, EuroStoxx 50 call options, and Hang Seng Index put options	The proposed model reduces the MAPE by more than 50%, compared to other ML models	The proposed model created smaller delta-hedging errors	X
(Kitamura & Ebisuda, 1998)		The performance of an ANN in pricing American-style call options was poor.	X	X
(Malliaris & Salchenberger, 1993)	Option-price transactions data published in the Wall Street Journal – Jan 1 – Jun 30, 1990	OTM: Mean difference BS = 0.506, mean difference NN = -0.118 ITM: Mean difference BS = -0.102, mean difference NN = -0.499	X	X
(Park, Kim, & Lee, 2014)	KOSPI 200 Index options – Jan 2001 – Dec 2010	All ML methods outperform BS in terms of pricing error	X	X
(Phani, Chandra, & Raghav, 2011)	American option price for companies belonging to various sectors	The NN and the SVR out performed BS by 12.42 and 15.02 in terms of MAE	X	X
(Qi & Maddala, 1996)		The ANN approach is superior to the BS model	X	X
(Saxena, 2008)	Options traded at National Stock Exchange India Ltd.	ANN outperforms BS: ITM: ΔMAD = 19.0 OTM: ΔMAD = 16.164	X	X
(Stark, 2017)	DAX 30 call options – Jan 1, 2013 – Sep 19, 2017	ANN outperforms BS: ΔMAD = 5.566	ANN is superior in delta-hedging at a 5% significant level	X
(Yao, Li, & Tan, 2000)	Nikkei 225 Index futures	ANN mean NMSE = 0.018 BS mean NMSE = 0.021	X	X
RESULTS	23 Research Papers	ΔRMSE ≈ 65% ΔMAD ≈ 13.58 ΔMSPE ≈ 5-10%	ML's hedging performance is superior to the BS model ±30-40%	X

6.C Full results table of the meta-analysis on the application of machine learning in bond pricing

ARTICLE	SAMPLE	PERFORMANCE	RISK	GROWTH
(Bianchi, Büchner, & Tamoni, 2021)	U.S. Treasury Bills	Machine learning methods provide strong statistical evidence in factor of bond return predictability	X	A strongly positive coefficient of excess bond returns on uncertainty about economic growth was found
(Ganguli & Dunnmon, 2017)	762,678 bonds	ANNs and GLMs give the best results in terms of combined accuracy and speed	X	X
(Götze, Gürtler, & Witowski, 2020)	597 CAT bonds Jan, 2002-Dec, 2017	RF yields a considerably lower mean RMSE of 0.0087 than other models	The availability of risk assessment is among the potential causes for the good performance of linear regression models	X
(Guo, Lin, Wu, & Zhou, 2021)	LBFI database on corporate bonds Jan, 1973-Mar, 1998	It is more informationally efficient and capable of detecting a strong return predictability in the corporate bond market	The plausible source for the predictive power of the yield signal is its ability to predict changes in fundamentals that influence bond default risk	The trading strategy based on yield trend signals earns higher returns in periods of slow economic growth and recession
(He, Feng, Wang, & Wu, 2021)	19,782 unique bonds for public & private companies 1976-2017	The RF forecasts delivers a monthly return of 1.48% over a five-factor model	X	X
(Kratsios & Hyndman, 2020)	German bond data for 31 maturities	The ML model outperforms the rest by progressively	X	X

	Jan 4, 2010-Dec 30, 2014	larger margins: 2.749 x 10^{-24} vs 2.360 x 10^{-4}		
(Shen & Wang, 2011)	Xin-gang stock Sep 8, 2008-Dec 31, 2010	It is a beneficial attempt to integrate SVM and copula function to analyse the value of convertible bonds	X	X
RESULTS	7 Research Papers	Increased returns and reduced RMSEs show that ML methods are beneficial in bond pricing	ML method's ability to assess and predict risk improves the forecasting performance	The coefficient between returns and uncertainty about growth shows the link between ML and growth