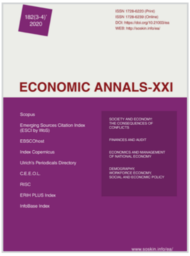

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A neural network approach for fundamental investment analysis: a case of Athens Stock Exchange

Abstract. This paper explores investment profitability in an emerging European stock market using fundamental analysis enhanced by artificial neural networks. Using a set of accounting-based financial ratios from publicly available data source, we find that these ratios possess useful information in forecasting future stock returns of Athens Stock Exchange (ATHEX) constituent firms. By combining long and short rules, the neurally reinforced fundamental strategy surpasses the unconditional buy-and-hold rule in the holdout subperiod in terms of returns (total and annualized) and risk (volatility, downside volatility and drawdown) measures. Overall results remain consistent even in the presence of trading costs. Our findings suggest that stock prices in Greece do not fully incorporate financial statement information and thus inconsistent with the principle of market efficiency at the semi-strong form.
Keywords: Fundamental Analysis; Financial Ratios; Neural Networks; Out-of-Sample; Athens Stock Exchange
JEL Classifications: C45; G14; G17
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Нейромережевий підхід до фундаментального інвестиційного аналізу: приклад Афінської фондової біржі

Анотація. У цій статті досліджується прибутковість інвестицій на європейському фондовому ринку, що розвивається, з використанням фундаментального аналізу, посиленого штучними нейронними мережами. Використовуючи набір фінансових коефіцієнтів на основі бухгалтерського обліку із загальнодоступних джерел даних, ми виявили, що ці коефіцієнти містять корисну інформацію для прогнозування майбутньої прибутковості акцій компаній, що котируються на Афінській фондовій біржі (ATHEX). Комбінуючи довгі й короткі правила, нейронно посилена фундаментальна стратегія перевершує безумовне правило покупки й утримання в підперіод утримання з точки зору показників прибутковості (загальних та річних) і ризику (волатильність, волатильність у бік зниження й просідання). Загальні результати залишаються стабільними навіть при наявності торгових витрат. Наші результати показують, що ціни на акції в Греції не повністю включають інформацію з фінансової звітності й, таким чином, несумісні з принципом ринкової ефективності в напіввисокій формі.
Ключові слова: фундаментальний аналіз; фінансові коефіцієнти; нейронні мережі; поза вибіркою; Афінська фондова біржа.

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Нейросетевой подход к фундаментальному инвестиционному анализу: пример Афинской фондовой биржи

Аннотация. В этой статье исследуется прибыльность инвестиций на развивающемся европейском фондовом рынке с использованием фундаментального анализа, усиленного искусственными нейронными сетями. Используя набор финансовых коэффициентов на основе бухгалтерского учета из общедоступных источников данных, мы обнаружили, что эти коэффициенты содержат полезную информацию для прогнозирования будущей доходности акций компаний, котирующихся на Афинской фондовой бирже (ATHEX). Комбинируя длинные и короткие правила, нейронно усиленная фундаментальная стратегия превосходит безусловное правило покупки и удержания в подпериод удержания с точки зрения показателей доходности (общей и годовой) и риска (волатильность, волатильность в сторону понижения и просадка). Общие результаты остаются стабильными даже при наличии торговых затрат. Наши результаты показывают, что цены на акции в Греции не полностью включают информацию из финансовой отчетности и, таким образом, несовместимы с принципом рыночной эффективности в полувысокой форме.

Ключевые слова: фундаментальный анализ; финансовые коэффициенты; нейронные сети; вне выборки; Афинская фондовая биржа.

1. Introduction

Financial market is a vital place for different investing individuals and entities to increase their wealth. Globally in 2019, over USD 200 billions worth of stocks were traded daily [1], thus the ability to predict their future prices (or returns) is an important subject and can aid investors to obtain significant profits. This task, however, proves to be very challenging given the dynamic nature, mechanisms and factors surrounding stock prices. Among others, these include uncertainties about the companies and the economic, social and political conditions. For these reasons, numerous ways and instruments have been invented by practitioners and academicians to forecast stock prices, and these fall within two categories: fundamental and technical analysis.

Our study focuses on predicting stock returns of listed companies in Greece using fundamental indicators enhanced by artificial neural networks. Fundamental analysis focuses on the underlying aspect of stocks such as financial profile of firms from news and financial statements deemed to have certain effects on the performance of stock prices [2-3]. The proponents of fundamental analysis hold the views that the analysis attempts to predict prices by emphasising on uncovering their intrinsic values through financial ratios [4-5]. This technique, however, is relatively less researched as compared to its counterpart, technical analysis. For example, Nti et al. (2020) [6] note that less than a quarter of the articles that they review use only fundamental analysis for predicting stock markets. Sloan (2019) [3] calls for future research on fundamental analysis especially after a large number of researches find certain financial ratios have relations to future stock returns. As this suggest the much potential of fundamental analysis, he further warns on the over-simplification of analysis that rely on simple financial ratios and uses unrealistic assumptions [3]. On a similar note, Gepp et al. (2020) [7] highlight on the limitations of traditional approaches that assume linear relationship between variables.

To address the above issues, many authors argue in support of artificial neural networks as an effective tool to deal with market volatility, complexity and noisy environments [6, 8]. In fact, several studies find that such neurally enhanced strategy generates greater returns [9-10]. This paper attempts to contribute to the literature in this domain. Specifically, we train a neural network in-sample using publicly available financial ratios to predict out-of-sample stock returns for the constituent firms in ATHEX. For robustness, we use out-of-sample test and explore long-only, short-only and both rules against the passive buy-and-hold (B&H) investment policy and employ several performance measurement techniques in the absence and presence of trading costs, in gauging the efficacy of the fundamental trading strategy.

Our paper proceeds as follows. Section 2 gives a short account of related literature. Purpose is outlined in Section 3. This is followed by the results in Section 4. Section 5 concludes.

2. Brief Literature Review

The basic premise of the semi-strong form efficient market hypothesis (EMH) claims that stock prices at any given time reflect all publicly available information, as posited by Fama (1965, 1970) [11-12]. This includes financial statement data which is the foundation of fundamental-based investment strategies. Consequently, the theory asserts that such analysis cannot yield abnormal returns over the market on a consistent basis. As a result, if such strategy indeed dominates the B&H rule, the market is said to contradict the EMH at the semi-strong form.

This contention continues to be debated by the researchers where a number of studies document that fundamental analysis is a good predictor of stock returns [4, 9-10]. In Greece, with the exception of Alexakis et al. (2010) [13], our observation (using related keywords from Scopus database) reveals there is no other research focusing on fundamental analysis. Subsequently, the use of such strategy within the context of machine learning is non-existent. In this regard, the Greek stock market is thus still underexplored in the literature. And as an emerging European economy, it may yet offer potential lucrative returns for investors.

3. The purpose of this article is to design and train a neural network using fundamental indicators to predict future (annual) stock returns in the emerging Greek market, and consequently examine its profitability. Using individual stocks in the ATHEX, we investigate the neurally enhanced trading rules using several performance measures in the blind holdout subperiod.

4. Results

Our whole sample spans 01/07/2010 to 30/06/2020 which is very recent and captures different country-level and global episodes including the recent COVID-19 pandemic. Historical stock prices and financial ratios are obtained from Morningstar database, which include return on assets (ROA), return on equity (ROE), return on invested capital (ROI), current ratio (CRN), debt to equity (DEQ) and free cash flows to sales (FCS). Data are then filtered to ensure sufficient time-series and fundamental information for valid analysis, which results in a total of 79 sample firms. We further separate the period into two non-overlapping subperiods. The first subsample spans 01/07/2010 to 30/06/2018 (in-sample) which is utilized to train the neural network. The second subsample (out-of-sample) from 01/06/2018 to 30/06/2020 is used to test the performance of our fundamental neural network (FANN) trading rule. This data splitting allows us to evaluate if FANN trained using in-sample data can be employed to yield economically significant returns in the blind out-of-sample period.

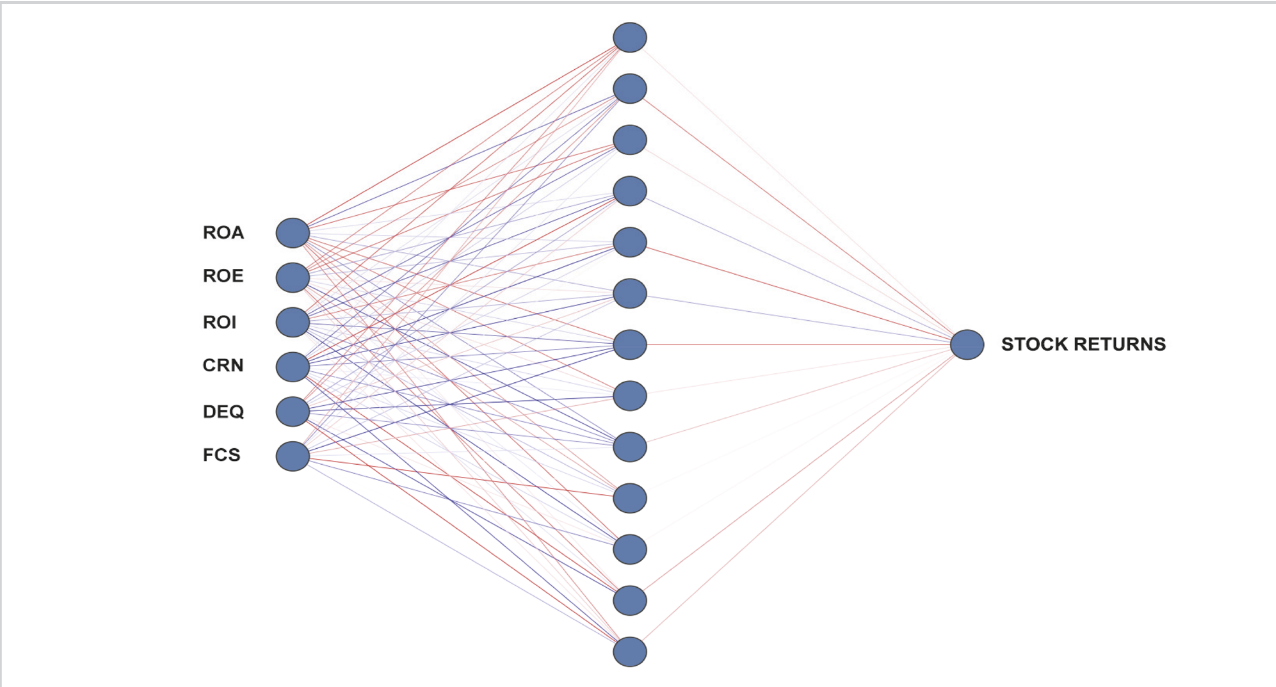
Due to its widespread use, we use the multilayer feedforward neural networks with the back-propagation algorithm [14]. This allows for comparability and replication of our approach. The FANN uses logistic sigmoid function as its activation function, while our network architecture is based on N number of variables (financial ratios) in the input vector with a single hidden layer [15] of 2N+1 hidden nodes based on Kolmogorov theorem [16], and a single output (1-year stock returns). Figure 1 shows the network architecture of the FANN.

The topology below shows how the six financial ratios are used as inputs to the FANN to build the fundamental neural network and predict future stock returns. The 1-year forecasting length or annual returns used for fundamental analysis is consistent with prior literature such as [9] and practice i.e. audited financial statements are often available on a yearly basis. Recall that we train the network using the in-sample period. The network learns by comparing the differences between its predicted and actual returns on the basis of the mean squared error (MSE) and adjusting the weights through the momentum and training factors. This training progress is depicted in Figure 2.

The network stops learning when there is no further improvement in its MSE for consecutive 1,000 epochs to avoid overfitting and to preserve its generalisation ability. Accordingly, FANN runs for 15,422 epochs and as exhibited in Figure 2, its final MSE in predicting 1-year stock returns is lower than 0.0013. By using the in-sample trained network, we form the appropriate entry (exit) rules for out-of-sample forecasting by distinguishing the boundary between positive and negative average outputs to emit buying and selling signals.

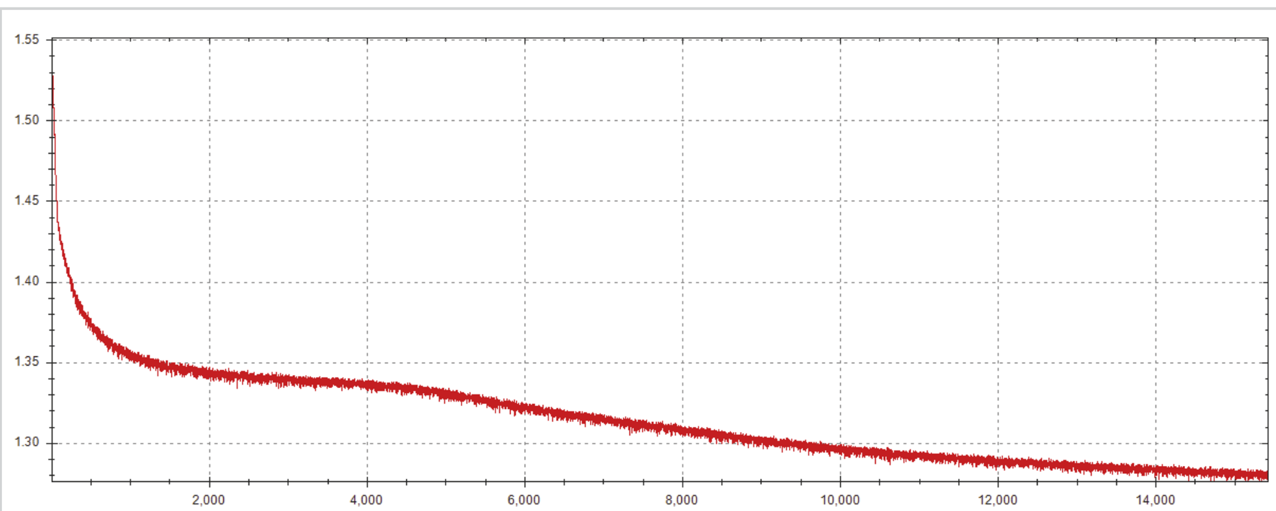
In practice, retail investors (and even institutional ones) have limited capital, so it is unrealistic to assume that they can buy any stock without any budget constraint whenever undervaluation is detected. As such, to execute practical trading simulation, we consider a EUR 100,000 portfolio fund. Because trading costs play an important part for earning returns especially in the context of active investments, we investigate the capability of FANN with and without a 2% round-trip fee to see if returns dissipate significantly in the economic sense. Furthermore, long only (FANN-L) and short only (FANN-S) strategies are also investigated. Note that FANN comprises both long and short investment rules. Finally, consistent with literature in this field, the passive buy-and-hold (B&H) strategy is used as benchmark as it signifies the best policy under the assumption that the market is information efficient.

Table 1 shows the trading performance (without any fees) for FANN, FANN-L, FANN-S and B&H during the out-of-sample period. Briefly stated, fundamental trading strategy enhanced using



Note: The figure shows the network topology for FANN with 6 inputs (financial ratios), 13 hidden nodes in a single hidden layer and 1 output (annual stock returns). Colour differences in the lines indicate positive (blue) and negative (red) weights and are provided for illustration purpose.

Figure 1:
FANN architecture
Source: Analysed by the authors



Note: The figure shows neural network training for the FANN.
The y-axis indicates MSE × 1,000 while x-axis denotes the epochs.

Figure 2:
FANN training performance
Source: Analysed by the authors

neural network earn highest returns and annualized returns (EUR 13,648.07 and 6.62%, respectively), as well as better i.e. lower maximum drawdown (less than a third of B&H) and coefficient of variation. Yet it is important to stress that such performance comes from capitalising on both upward and downward directions of the market. For example, both long-only and short-only rules (i.e. FANN-L and FANN-S) underperform the B&H. However, more than 70% of the trades signalled by the FANN-S produce profitable outcomes and it gives the highest average returns when the network predicts that stock prices are falling.

To see if our results hold in the presence of trading costs, we consider round-trip (buy and sell) fees where the results are displayed in Table 2. Even with costs, the performance is similar. FANN earns highest returns (EUR 11,018.19) and annualized returns (5.38%), coupled with lower maximum drawdown (-9.25%) and coefficient of variation (1.4493). In short, FANN produces the best profit measures, lowest peak to valley decline and lowest variability against returns as compared to the benchmark B&H policy and the long-only and short-only rules. Evidently, the returns are smaller because buy and sell transactions are subject to fees. Regardless, like the no-fees simulation, their outperformance as compared to the B&H policy is attributed to capturing both long and short investment potentials.

As can be seen from the results on machine learning-based fundamental trading rule, the long-only, short-only and strategy using both long and short signals earn better returns (and lower risks) when compared to the passive benchmark rule. In dissecting this finding on a firm level, Figure 3 shows the heatmaps of mean returns for each traded component firm from trading using signals emitted by the FANN rule (with and without trading costs). Noticeably, some

Table 1:
Trading performance of the fundamental analysis neural network and buy-and-hold rule (without fees)

	FANN	FANN-L	FANN-S	B&H
Total Returns (EUR)	13,648.07^	7,801.47	5,846.60	9,112.72
Annualized Returns (%)	6.62^	3.84	2.89	4.47
Mean Returns (EUR)	192.23	165.99	243.61^	115.35
Profitable Trades (%)	57.75	51.06	70.83^	49.37
Maximum Drawdown (%)	-11.34^	-26.12	-12.42	-36.94
Coefficient of Variation	1.3514^	3.1250	2.7778	3.2258

Note: Table shows trading performance of FANN, FANN-L, FANN-S and B&H during the out-of-sample period from 01/07/2018 to 30/06/2020 with trading fees. Total returns indicate profits received from trading the EUR 100,000 investment capital. Annualized returns show the geometric average of profit by an investment. Mean returns refer to average returns for each trade. Profitable trades indicate the proportion of trades (out of all trades) which generate positive returns. Maximum drawdown indicates the largest peak to valley decline during the period. Coefficient of variation indicates the extent of variability of trading returns as compared to its mean. ^ indicates better performance outcome for each measure.

Source: Computed by the authors

Table 2:
Trading performance of the fundamental analysis neural network and buy-and-hold rule (with fees)

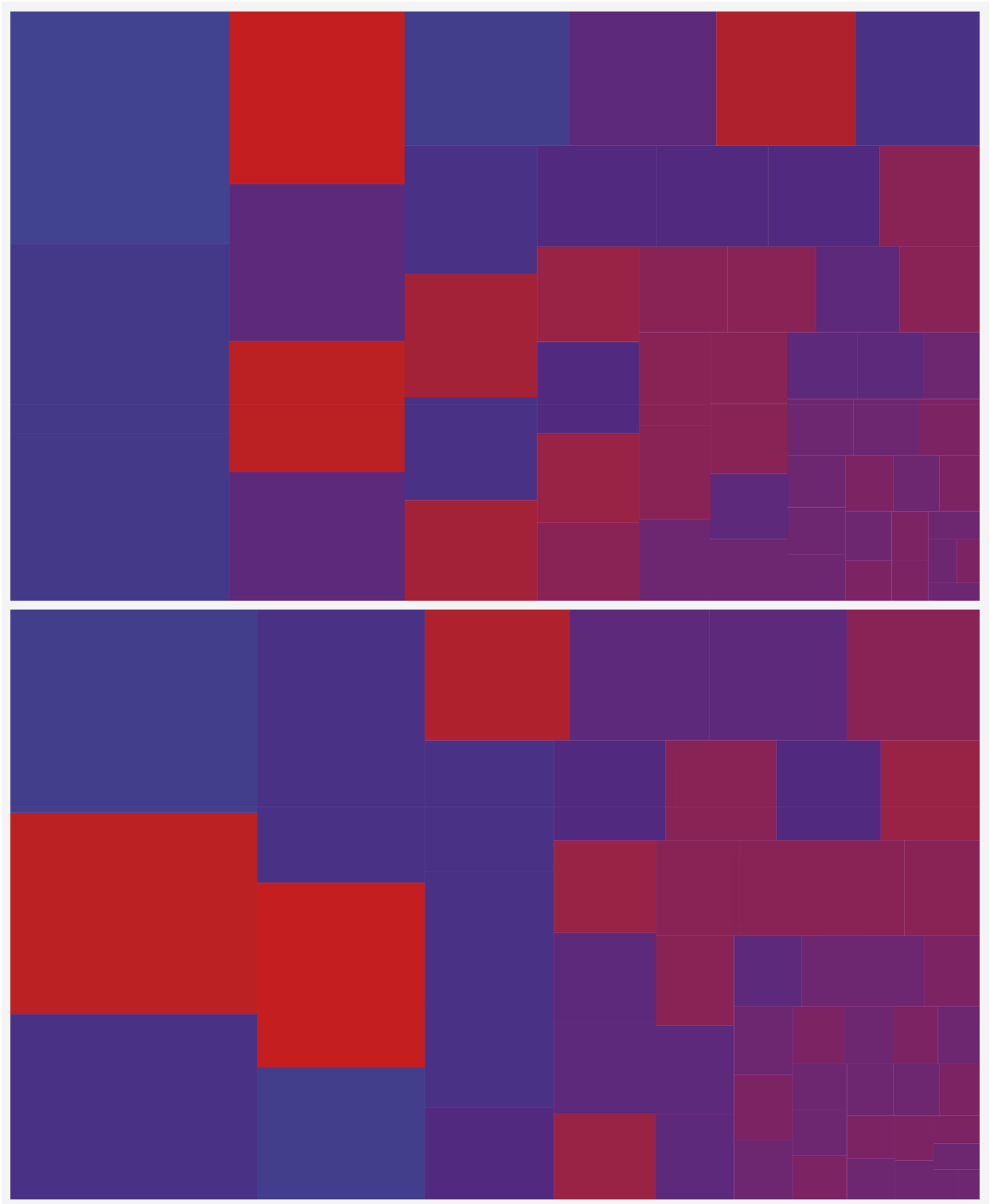
	FANN	FANN-L	FANN-S	B&H
Total Returns (EUR)	11,018.19^	8,642.71	2,375.48	8,116.75
Annualized Returns (%)	5.38^	4.24	1.18	3.99
Mean Returns (EUR)	157.40	192.06^	95.02	102.74
Profitable Trades (%)	60.00	55.56	68.00^	49.37
Maximum Drawdown (%)	-9.25^	-25.09	-16.34	-37.20
Coefficient of Variation	1.4493^	2.8571	6.2500	3.4483

Note: Table shows trading performance of FANN, FANN-L, FANN-S and B&H during the out-of-sample period from 01/07/2018 to 30/06/2020 with trading fees. Total returns indicate profits received from trading the EUR 100,000 investment capital. Annualized returns show the geometric average of profit by an investment. Mean returns refer to average returns for each trade. Profitable trades indicate the proportion of trades (out of all trades) which generate positive returns. Maximum drawdown indicates the largest peak to valley decline during the period. Coefficient of variation indicates the extent of variability of trading returns as compared to its mean. ^ indicates better performance outcome for each measure.

Source: Computed by the authors

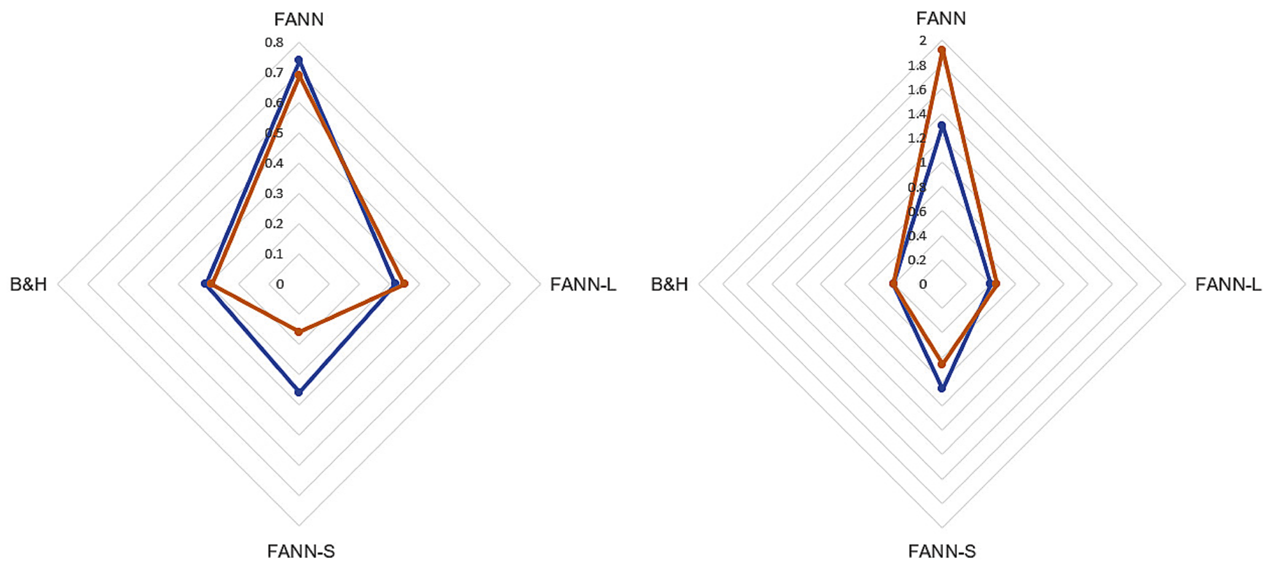
firms contribute to a greater portion of returns to the overall portfolio, gravitating towards profitable trades. This suggests that the neural network can identify patterns to buy (short sell) undervalued (overvalued) stocks with greater magnitudes in positive returns, while smaller profits or losses can be seen distributed somewhat evenly among the rest of the stocks.

Although FANN can offer positive returns, it is important to stress that profit alone is not a sufficient sign to confirm the superiority of a particular strategy. For instance, investors have different risk aversion levels. This means their acceptance of a particular asset or stock investment may differ due to some underlying risk factors, despite having identical returns. Hence, returns from trading must also be assessed in accordance with its risk (i.e. risk-return trade-off) before any finding can be said as economically significant. To this end, Figure 4 depicts two popular measures, Sharpe and Sortino ratios, under the scenarios of with and without fees.



Note: The figures show the mean returns of trading using the FANN strategy during the out-of-sample period (01/07/2018 to 30/06/2020). Top (bottom) chart reflects the performance without (with) transaction costs. Blue (red) colour shows mean profit (loss) of each company. Larger size indicates greater profit or loss.

Figure 3:
FANN mean return heatmaps
Source: Computed and elaborated by the authors



(a) Sharpe Ratio **(b) Sortino Ratio**

Note: The charts denote performance measures based on return and volatility (Sharpe ratio) as well as return and downside volatility (Sortino ratio) from trading individual stocks in the ATHEX. Blue (orange) lines indicate trading simulation without (with) transaction fees.

Figure 4:
Risk-return performance measures
Source: Analysed by the authors

As shown in the figure, FANN clearly dominates the B&H rule in both cases. Although FANN-L and FANN-S rules do not indicate supremacy, FANN obtains a Sharpe ratio of 0.74 (0.69) versus 0.31 (0.29) produced by the passive benchmark without (with) cost. Put another way, for the same level of risk, FANN generates over twice the return against simply buying and holding stocks. In similar vein, Sortino ratio confirms the effectiveness of FANN with values of 1.3 (1.92) without (with) fees as compared to the B&H policy with 0.4 in both cases. Stated differently, when negative deviation of returns is concerned, FANN further outperforms B&H as its return is over triple (without fees) and quadruple (with fees) to that of the latter for the same unit of risk. One possible explanation of better outperformance when fees are considered is due to random omission of some unprofitable trades from reduced capital after subtracting the costs. This notion is corroborated by the data. All in all, our results confirm that the fundamental neural network which attempts to gain from buying undervalued stocks and simultaneously short selling overvalued ones provide greater return to variability.

5. Conclusion

In this article we train a neural network using a set of fundamental indicators and explore its trading performance in the emerging stock market of Greece. Based on publicly available data of 79 constituent firms listed in ATHEX over the period mid-2010 to mid-2020 (with the last 2 years as the holdout subperiod), we explore long-only (FANN-L), short-only (FANN-S) and both rules (FANN) against the unconditional B&H benchmark rule. We find that while the neural-based unidirectional strategies come with profits, they generally underperform the passive benchmark. However, the FANN strategy which capitalises on both signals that the market is going up and down distinctly surpasses the B&H in terms of returns and risks measures, even when the round-trip trading cost is considered.

Our findings add to prior research in Greece by [13] and suggest that the neural network is capable to learn the nonlinear relationship between financial ratios and future stock returns, and the outcome is not ascribed to higher risk. The results infer that ATHEX is semi-strong inefficient where market prices deviate from their intrinsic values and do not react instantaneously to publicly available financial statement information. In other words, undervaluation or overvaluation may persist for a lengthy time, allowing investors to exploit market inefficiency. Further research can be undertaken in areas such as utilizing different sets of financial variables, equity markets and machine learning techniques, as well as incorporating various performance measures and risk management policy.

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