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Machine learning methods for financial forecasting and trading profitability: Evidence during the Russia–Ukraine war

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Abstract

Purpose – This study aims to evaluate the effectiveness of machine learning models to yield profitability over the market benchmark, notably in periods of systemic instability, such as the ongoing war between Russia and Ukraine.

Design/methodology/approach – This study made computational experiments using support vector machine (SVM) classifiers to predict stock price movements for three financial markets and construct profitable trading strategies to subsidize investors' decision-making.

Findings – On average, machine learning models outperformed the market benchmarks during the more volatile period of the Russia–Ukraine war, but not during the period before the conflict. Moreover, the hyperparameter combinations for which the profitability is superior were found to be highly sensitive to small variations during the model training process.

Practical implications – Investors should proceed with caution when applying machine learning models for stock price forecasting and trading recommendations, as their superior performance for volatile periods – in terms of generating abnormal gains over the market – was not observed for a period of relative stability in the economy.

Originality/value – This paper's approach to search for financial strategies that succeed in outperforming the market provides empirical evidence about the effectiveness of state-of-the-art machine learning techniques before and after the conflict deflagration, which is of potential value for researchers in quantitative finance and market professionals who operate in the financial segment.

Keywords Time-series forecasting, Algorithmic trading, Support vector machines, Russia–Ukraine war, Efficient market hypothesis, Trading profitability

Paper type Research paper

1. Introduction

Machine learning applications in quantitative finance are increasingly frequent, both as a research topic and as practical tools to assist the decision-making of investors and market professionals. The technological improvements that allowed faster decision-making and the processing of a larger volume of information also boosted the development of methods and

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tools in various fields of finance, such as time-series forecasting, risk management, algorithmic trading, automated fraud detection and sentiment analysis (Emerson, Kennedy, O'Shea, & O'Brien, 2019; Dixon, Halperin, & Bilokon, 2020; Ozbayoglu, Gudelek, & Sezer, 2020).

One key aspect of machine learning models is their versatility to adapt to the data, with few or no assumptions regarding data distribution or the functional forms of the decision functions. However, while this flexibility allows the identification of more complex patterns, it also makes these models harder to control, especially for forecasting tasks (Probst, Boulesteix, & Bischl, 2019; Weerts, Mueller, & Vanschoren, 2020; Peng & Nagata, 2020), as small variations on the hyperparameter settings can have a strong impact on the fitted model and consequently on its outcomes, especially when machine learning methods are integrated into automated trading systems, as it has been increasingly usual both as a research topic and as an investing tool (Hilbert & Darmon, 2020; Min & Borch, 2022; Tao, Su, Xiao, Dai, & Khalid, 2021).

While the efficient market hypothesis (Fama, 1970), one of the cornerstones of finance theory, states that no individual agent can systematically outperform the financial market (under different assumptions of information availability), a big number of recent papers have reported success in "beating the market" through the usage of machine learning algorithms for a wide range of markets and time periods (Dastile, Celik, & Potsane, 2020; Bustos & Pomares-Quimbaya, 2020). On the other hand, even under the efficient market hypothesis, brief opportunities to yield gain over the financial market are possible when the whole market undergoes sudden oscillations as a consequence of a structural break in the financial time-series or as a result of an event that triggers systematic implications. An example of such an event is the ongoing military conflict between Russia and Ukraine, which began in late February 2022 and has brought a huge impact not only on the global economy but also on the international geopolitical configuration.

In this context, this paper aims to investigate the predictive power of machine learning models for financial time-series, evaluating their out-of-sample performance both in terms of forecasting and profitability for a potential investor that would make trading operations in the financial market following their suggestions. Therefore, this paper's main contribution is to compare the predictive performance and profitability of the models before the deflagration of the Russia–Ukraine war with their performance during the period of war to analyze whether a systematic disturbance in the data-generating processes has affected the overall effectiveness of machine learning models, as well as to find additional insights about market efficiency and propensity to yield gains above the market level.

2. Theoretical background

2.1 Machine learning in stock price forecasting

The application of machine learning methods in quantitative finance has been increasingly popular in the recent literature, due to the flexibility of this class of models and their ability to yield better empirical performance compared to well-known models from classic econometrics, as discussed by works like Hsu, Lessmann, Sung, Ma and Johnson (2016), De Spiegeleer, Madan, Reyners and Schoutens (2018), Peng, Albuquerque, de Sá, Padula and Montenegro (2018) and Albuquerque, de Moraes Souza and Kimura (2021). Other notable recent applications in financial contexts include: Kozak, Nagel and Santosh (2020), which incorporated nonlinear interactions into classic asset pricing models and applied dimensionality reduction techniques to find the main principal components that were able to capture most of the relevant information; Renault (2020), which analyzed the correlation between investor sentiment and stock returns based on texts messages collected from a social media directed to the traders' community; and Gu, Kelly and

Xiu (2020), which compared regularized linear models and machine learning algorithms to model the risk premium of financial assets incorporating nonlinear interactions and variance shrinkage techniques. In-depth compendiums of the recent literature on machine learning applications in quantitative finance can be found in the survey papers of Dastile *et al.* (2020), Ozbayoglu *et al.* (2020), Gogas and Papadimitriou (2021) and Goodell, Kumar, Lim and Pattnaik (2021).

One critical aspect of empirical applications of machine learning models is to maximize their generalization ability, by finding the ideal balance between in-sample fitness and complexity – often known as the bias-variance dilemma. As discussed in Claesen and De Moor (2015), Probst *et al.* (2019) and Peng and Nagata (2020), small changes in the hyperparameter settings of a machine learning experiment can lead to significant differences in the resulting decision function and finding the optimal combination of hyperparameters that minimize the out-of-sample generalization error is one of the main empirical challenges for machine learning experiments.

In the task of financial time-series forecasting, while technical analysis features are built using basic variables such as daily closing price and traded volume, the stylized facts of financial returns and the explanatory power coming from nonlinear dependences, apart from the usual challenges of serial correlation and heteroscedasticity, motivate the application of machine learning methods to forecasting the price trends and build profitable trading strategies (Vijh, Chandola, Tikkiwal, & Kumar, 2020; Ghasemzadeha, Mohammad-Karimi, & Ansari-Samani, 2020).

The emergence of machine learning methods as a popular paradigm for financial analysis and the advancements in computational power and accessibility has boosted interest in research and development of automated trading recommendation systems, which are often designed to process a high number of features, especially when high-frequency trading is considered. As pointed out by Taghian, Asadi and Safabakhsh (2022), the flexibility of machine learning methods also demands caution from the researcher when defining the model parameters and architectures; specifically, the authors discussed the effects of input representations and feature extraction in deep reinforcement learning methods and proposed an asset-specific framework that managed to outperform the best benchmark model in more than 12% in terms of profitability.

Aligned to that, Ayala, García-Torres, Noguera, Gómez-Vela and Divina (2021) proposed a hybrid approach to generate trading signals by applying a technical indicator combined with a machine learning approach to generate a trading signal. Apart from standard linear models, artificial neural networks, random forests and support vector regression were considered as base-learners. Using data from three financial indexes, the authors reported that the addition of machine learning techniques to technical analysis strategies improved the profitability of the yielded trading recommendations.

As discussed in Peng, Albuquerque, Kimura and Saavedra (2021), both specialized literature and market professionals have identified a great number of technical analysis indicators that serve as candidate predictors for future stock prices, which also motivated the application of feature selection to eliminate redundant or non-informative features prior to the training of the machine learning algorithms – in this case, deep neural networks with dropout regularization. Haq, Zeb, Lei and Zhang (2021) performed similar experiments, first ordering the indicators by their relative importance through independently training logistic regressions, support vector machines (SVMs) and random forests and then applying a deep generative model with a market signal decoder and a noise discriminator based on attention mechanism. Examples of survey papers of recent articles that tackled the stock market forecast using technical analysis indicators can be found in Nti, Adekoya and Weyori (2020), Li and Bastos (2020) and Bustos and Pomares-Quimbaya (2020).

2.2 The 2022 Russia–Ukraine war: background, chronology and impacts on the global market

In order to further evaluate whether machine learning methods are effective in generating winning trading strategies in periods of notable turbulence in the world market, this paper considered an out-of-sample period in which the Russia–Ukraine war is underway, an event with relevant implications to the international economy and to the global financial market.

A relevant milestone of the relationship between Russia and Ukraine after the end of the cold war was the Orange Revolution, a series of political protests organized in response to the results of the 2004 Ukrainian presidential election, in which pro-Russian candidate Viktor Yanukovych claimed victory amidst claims of corruption and electoral fraud. Centered in the Ukrainian capital city Kyiv and articulated by supporters of pro-Western candidate Viktor Yushchenko, the protests triggered a nationwide chain of strikes and acts of civil disobedience. A revote was ordered by the Ukraine Supreme Court and took place in December 2004, with Yushchenko being declared the winner (Karatnycky, 2005). The Orange Revolution boosted Ukraine's press freedom but also highlighted the existence of a polarization between groups that argued in favor of an approximation to Russia and enthusiasts of an approximation to Western coalitions such as the European Union and North Atlantic Treaty Organization (NATO) (Khodunov, 2022). This polarization was reflected in the very next elections for the Ukrainian parliament that took place in 2007 and escalated after Yanukovych was eventually elected for the presidency in 2010 (White & McAllister, 2009).

The Russia-Ukraine tensions reached a high point in 2014, when Russia conducted a lightning operation that ended with the annexation of the Crimean Autonomous Republic, an act that was considered an act of "dangerous and preclusive imperialism" by some critics of Russia (Gardner, 2016) and "a severe violation of international law" even by some pro-Russian groups (Saluschev, 2014). This event triggered a political crisis in Eastern Europe and represented a shift of the Russian international policy away from Europe and the United States and toward China, as seen through the signing of a 30-year gas agreement between Russia and China after the annexation (Biersack & O'lear, 2014). Moreover, the Crimea crisis aggravated the polarization of Ukraine between integration towards Russia or Europe, consequently augmenting the clash between the security interests of these two geopolitical forces (Nitoiu, 2016), eventually leading to the Russian military engagement against Ukraine on February 24, 2022. Since then, Russian forces bombed several Ukrainian administrative headquarters and part of a building that houses the Zaporizhzhia nuclear power plant, while Ukrainian president Volodymyr Zelenskyy accused Russia of genocide after hundreds of civilian bodies were found in Bucha and Mariupol. Russia suffered a series of economic sanctions and eventually began to also apply sanctions to Europe regarding the supply of natural gas and energy.

As for the economic dimension, Russia produces approximately 10% of the world's petroleum and is a major energy exporter to Europe, to where it represents the origin of 24.7% of the petroleum imports and 46.8% of the natural gas imports (Lodi *et al.*, 2022). Additionally, Russia and Ukraine are also relevant producers of crops: Ukraine alone is responsible for more than 18% of the world exports of wheat, whilst Russia and Ukraine combine for more than 15% of the world exports of corn (Lodi *et al.*, 2022). Therefore, the armed conflict between these two countries not only severely affects the price of these commodities but also impacts the price of substitute goods such as soybeans and of animal protein, inducing worldwide impacts on commodity market and on the prices in general (Orhan, 2022; Saâdaoui, Jabeur, & Goodell, 2022). Apart from the impacts on the commodity prices, the conflict induced a severe shortfall in the world's supply of fertilizers for agricultural use, arousing additional concerns about global food security (Berkhout, Bergevoet, & van Berkum, 2022; Najafova, 2022).

Given the impacts of the conflict on the international economy, machine learning models trained under a wide range of hyperparameter settings were applied for the empirical analysis, comparing the results obtained for two out-of-sample periods: one before the outbreak of the war and another after the first Russian offensive on Ukraine. The methods employed in this paper and the execution steps of the experiments are described in the next section.

3. Methods and empirical analysis

In this paper, the SVM classifier (Boser, Guyon, & Vapnik, 1992; Cortes & Vapnik, 1995) was chosen for the empirical experiments; this choice was motivated by the results reported in Probst *et al.* (2019), in which SVM was the machine learning model with the highest average hyperparameter tunability – that is, the model with the largest potential performance gain arising from changes in the hyperparameters. SVM is a supervised learning algorithm commonly used in the recent machine learning literature. For the general case in which the data may not be linearly separable, SVM can be applied to a set of data mapped to a high-dimensional feature space using Kernel functions, providing this model with higher flexibility to learn more complex patterns. As defined in Cortes and Vapnik (1995), SVM solves the following convex quadratic programming problem:

$$\begin{gathered} \textit{Minimize}: \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\boldsymbol{\xi}^T\mathbf{1} \\ \textit{Subject to}: \boldsymbol{D}(\Phi\boldsymbol{w} - b\mathbf{1}) \geq 1 - \boldsymbol{\xi} \\ b \in \mathbb{R}, \boldsymbol{w} \in \mathbb{R}^q, \boldsymbol{\xi} \geq 0 \end{gathered} \tag{1}$$

where $C \in \mathbb{R}^+$ is a user-defined hyperparameter that represents the penalization for misclassified observations, $\boldsymbol{\xi}$ is a vector of slack variables, $\boldsymbol{D}$ is the diagonal square matrix of the class labels for each observation, $\boldsymbol{\Phi}$ is the matrix of nonlinear mapping applied to each pair of observations $\boldsymbol{x_i}$ and $\boldsymbol{x_j}$, $i, j = 1, 2, 3 \ldots, n$ and n is the sample size. This optimization problem has a global optimal solution, and the decision function of the SVM classifier is given by Cortes and Vapnik (1995):

$$f(\boldsymbol{x_i}) = sgn\left(\sum_{i=1}^{n} \kappa(\boldsymbol{x_i}, \boldsymbol{x_j}) y_i \lambda_i - b\right) \tag{2}$$

where $sgn(.)$ is the sign function, $\kappa(\boldsymbol{x_i}, \boldsymbol{x_j}) = \varphi(\boldsymbol{x_i}) \cdot \varphi(\boldsymbol{x_j}) \in \mathbb{R}, i, j = 1, 2, 3 \ldots, n$ is the Kernel function that generalizes the inner product of the mapping φ for each pair of observations, $y_i \in -1, +1$ is the label of the i-th observation, λ_i is the i-th Lagrange multiplier and $b \in \mathbb{R}$ is the bias term (intercept) of the decision function. In this paper, the experiments will consider the Gaussian Kernel (also known as the "Radial Kernel" or "RBF Kernel"), which implicitly generalizes all polynomial interaction terms between $\boldsymbol{x}$ up to the infinite-dimension. The expression for the Gaussian Kernel is given by Peng and Nagata (2020):

$$\kappa(\boldsymbol{x_i}, \boldsymbol{x_j}) = exp\left(-\frac{\|\boldsymbol{x_i} - \boldsymbol{x_j}\|}{2\sigma^2}\right) \tag{3}$$

where $\sigma \in \mathbb{R}^+$ is a user-specified hyperparameter. As discussed in subsection 2.1, the choice of the hyperparameters C and σ can have a significant impact on the resulting decision function, thus influencing the predictions and the financial decision-making, even for convex methods that have an analytical solution, like SVM. In this sense, a vast number of hyperparameter combinations were tested in the empirical analysis to verify the impacts on out-of-sample classification and on the profitability of an investor that decides to follow the recommendations of the respective models.

For the empirical analysis, daily data between April 1st, 2021 and September 30th, 2022, were collected for firms from three financial indexes – Dow Jones Industrial Average, EURO STOXX 50 and Bovespa, representing the American, European and Brazilian markets, respectively. After the collection, each dataset was split into three sequential and mutually exclusive subsets, namely:

(1) Training set – observations between April 1st, 2021 and November 30th, 2021. This subset represented the in-sample portion of the data, thus being used to fit the machine learning models which were then applied to the two out-of-sample portions of the data;

(2) Test set 1 (pre-war period) – observations between December 1st, 2021 and February 23rd, 2022. This subset represents the out-of-sample period before the start of the Russia–Ukraine war;

(3) Test set 2 (war period) – observations between February 24th, 2022 and September 30th, 2022. Finally, this subset represents the out-of-sample period after the conflict began with the first Russian offensive against Ukraine on February 24, 2022.

The models trained using the first data subset were applied to two different portions of the data in order to analyze their effectiveness, by comparing a non-war period to a war period, both in terms of predictive performance and in terms of actual profitability that an investor would obtain if he/she had followed the trading operations indicated by the respective model. For all three subsets, the dependent variable (target variable) was the price direction movement between periods t and $t+1$, while the set of independent variables (features) was composed of 9 technical analysis indicators commonly utilized in the recent literature of machine learning models applied to financial forecasting, as displayed in Table 1.

To evaluate the robustness of each model, 10-fold cross-validation was applied to the training set, following the procedure described in Bergmeir and Benítez (2012). The respective decision functions were applied to the observations from the test set; for each hyperparameter combination, a different optimal model was trained and applied for the two out-of-sample data subsets. The hyperparameter tuning was performed with grid search, with the interval $[10^0, 10^{0.25}, \ldots, 10^{9.75}, 10^{10}]$ for hyperparameter C and $[0.25, 0.5, \ldots, 9.75, 10]$ for hyperparameter σ.

4. Results and discussion

Figures 1 and 2 present the profitability of the machine learning models trained under each hyperparameter combination for the test sets (pre-war and during the war) over the buy-and-hold strategy over the respective periods for the three analyzed markets – that is, the heatmaps show their respective out-of-sample profitability for each combination of C and σ. The buy-and-hold strategy involves buying a stock or a portfolio of stocks and retaining it, aiming at obtaining gains in the long term; thus, following this strategy is equivalent to purchasing an equally-diversified 1/n portfolio over the whole extension of the two test sets (Peng *et al.*, 2021).

Figures 1 and 2 represent the profitability over the buy-and-hold strategy for the three markets before and during the war, respectively. The blue tones represent the strategies that managed to yield gains over buy-and-hold, the green tones represent an additional gain close to zero and the warm colors like yellow, orange and red represent a profitability that was smaller than the buy-and-hold strategy. As these figures show, the SVM models that generated abnormal gains over the buy-and-hold strategy exhibited were highly sensitive to

Table 1.
Technical analysis indicators used as independent variables and recent references

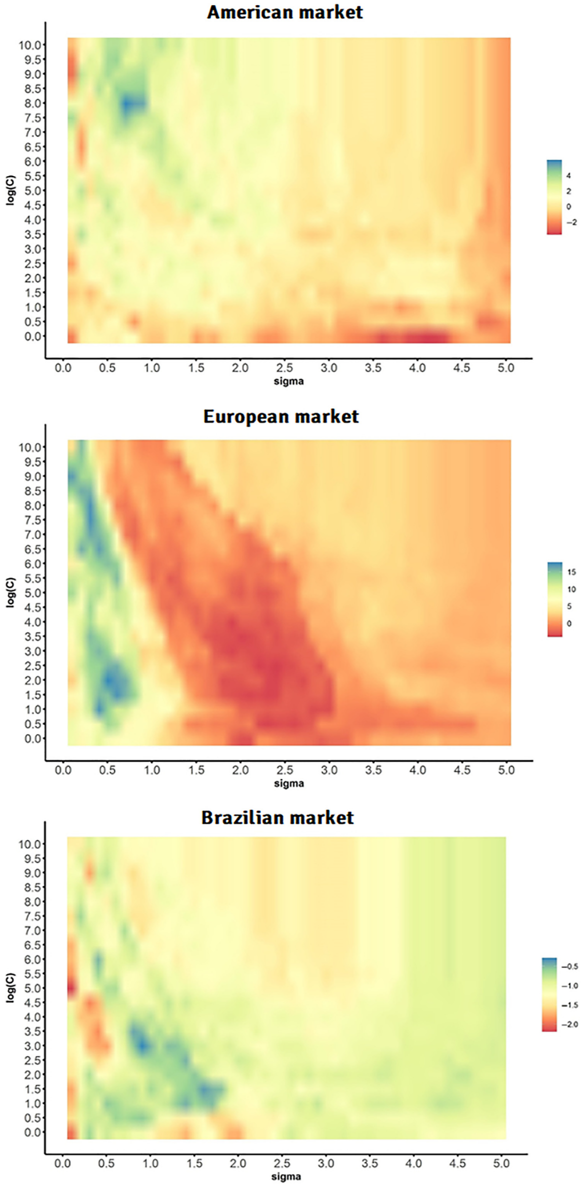
Independent variable	References
Simple moving average	Chen and Hao (2017), Gunduz, Yaslan, and Cataltepe (2017), Shynkevich, McGinnity, Coleman, Belatreche, and Li (2017), Weng, Ahmed, and Megahed (2017), Alhashel, Almudhaf, and Hansz (2018), Merello, Ratto, Oneto, and Cambria (2019), Sezer and Ozbayoglu (2018), Ghasemzadeha *et al.* (2020), Vijh *et al.* (2020) and Haq *et al.* (2021)
Exponential moving average	Chen, Xiao, Sun, and Wu (2017), Chen and Hao (2017), Gunduz *et al.* (2017), Shynkevich *et al.* (2017), Weng *et al.* (2017), Alhashel *et al.* (2018), Nakano, Takahashi, and Takahashi (2018), Sezer and Ozbayoglu (2018) and Haq *et al.* (2021)
Moving average convergence-divergence	Chen and Hao (2017), Gunduz *et al.* (2017), Alhashel *et al.* (2018), Nakano *et al.* (2018), Sezer and Ozbayoglu (2018), Ghasemzadeha *et al.* (2020), Ayala *et al.* (2021) and Haq *et al.* (2021)
Momentum	Gunduz *et al.* (2017), Weng *et al.* (2017), Merello *et al.* (2019) and Haq *et al.* (2021)
Rate of change	Gunduz *et al.* (2017), Shynkevich *et al.* (2017), Weng *et al.* (2017), Alhashel *et al.* (2018), Ghasemzadeha *et al.* (2020) and Haq *et al.* (2021)
On balance volume	Chen and Hao (2017), Nakano *et al.* (2018) and Sezer and Ozbayoglu (2018)
Relative strength index	Chen and Hao (2017), Gunduz *et al.* (2017) Weng *et al.* (2017), Shynkevich *et al.* (2017), Alhashel *et al.* (2018), Nakano *et al.* (2018), Sezer and Ozbayoglu (2018), Ghasemzadeha *et al.* (2020) and Haq *et al.* (2021)
Stochastic K%	Gunduz *et al.* (2017), Shynkevich *et al.* (2017), Alhashel *et al.* (2018) and Nakano *et al.* (2018)
William's R%	Gunduz *et al.* (2017), Shynkevich *et al.* (2017), Alhashel *et al.* (2018), Sezer and Ozbayoglu (2018) and Haq *et al.* (2021)

Source(s): Prepared by the authors

small variations in their hyperparameters – therefore, for these combinations it would be empirically possible to "beat the market". However, the hyperparameters for the best models did not follow a clear pattern that would also generate abnormal returns for future out-of-sample observations. From a statistical learning perspective, these findings are consistent with the high tunability values for SVM models reported in Probst *et al.* (2019) and the empirical implications of overfitting in machine learning experiments as discussed by Peng and Nagata (2020). From the perspective of finance theory, the setbacks in systematically generating models that outperform the market benchmark are also consistent with Fama (1970)'s classic result of Efficient Market Hypothesis.

Conversely, Table 2 summarizes some descriptive statistics about the strategies' profitability for the pre-war period and during the war period for the three markets, alongside the maximum value for the transaction costs for the investor to be able to break-even (TC_0) and to outperform the buy-and-hold strategy (TC_{BH}). Both TC_0 and TC_{BH} were calculated as the ratio between the cumulative gains over the period and the number of transactions performed. By assessing the strategies' profitability as a function of the maximum transaction cost under which a target profit is possible, this paper adds to the literature on machine learning applications in stock price prediction by determining the effectiveness of the models, based on the actual transaction costs from the respective markets, hence providing a more accurate measure of the models' impact on real-world decision-making.

For all three markets, Table 2 shows that in general terms the models exhibited a better performance during the war than before the war, with a greater proportion of models with better performance than the buy-and-hold profitability during that period. This pattern was consistent across all three markets but was especially stronger for the Brazilian market. In addition, the standard deviation of the models' profitability distribution was larger

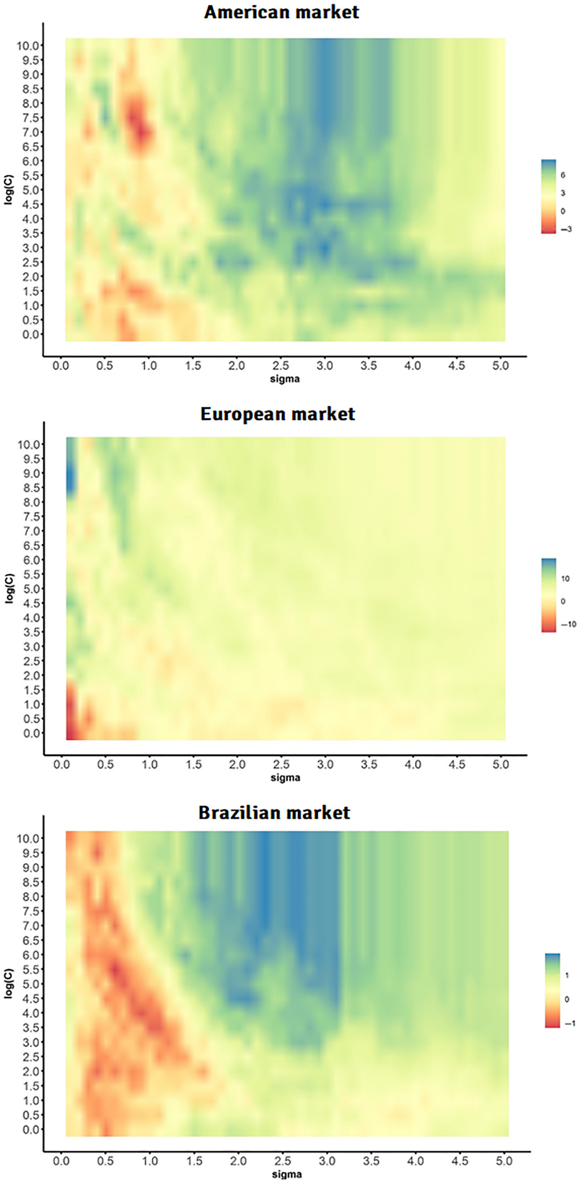


Source(s): Prepared by the authors

Figure 1.
Pre-war models' out-of-sample profitability over the buy-and-hold strategy for the three markets

during-war than pre-war for all three markets, an expected result given the implications of the conflict on the global economy.

The profitability values reported in Table 2 are only illustrative as it is unrealistic to operate in real-world trading without a benchmark strategy. In this sense, the sign and the magnitude of TC_{BH} are what really give away whether the models would effectively generate



Source(s): Prepared by the authors

Figure 2.
During-war models' out-of-sample profitability over the buy-and-hold strategy for the three markets

returns for the investor, with $TC_{BH} < 0$ implying that the investor would need to receive money for each operation to achieve the profitability of buy-and-hold on average, while $TC_{BH} > 0$ would represent the threshold value for individual transaction costs below which the investor would profit above the market benchmark.

Market	Period	Proportion of models that outperformed buy-and-hold (%)	Metric	Strategy profitability	TC_0	TC_{BH}
American	Pre-war	64.05	Maximum	1.49	0.07	0.27
			Median	−4.13	−0.20	0.02
			Minimum	−8.13	−0.56	−0.19
			Mean	−3.95	−0.19	0.02
			Standard deviation	1.36	0.07	0.07
	During-war	95.05	Maximum	2.85	0.07	0.21
			Median	−0.57	−0.01	0.12
			Minimum	−9.48	−0.20	−0.08
			Mean	−1.00	−0.02	0.11
			Standard deviation	2.20	0.05	0.05
European	Pre-war	72.45	Maximum	−1.34	−0.61	0.99
			Median	−2.95	−1.18	0.07
			Minimum	−3.52	−2.45	−0.17
			Mean	−2.88	−1.20	0.11
			Standard deviation	0.42	0.18	0.20
	During-war	94.67	Maximum	8.56	0.20	0.45
			Median	−5.55	−0.12	0.10
			Minimum	−23.84	−1.46	−0.84
			Mean	−5.61	−0.12	0.09
			Standard deviation	2.69	0.10	0.07
Brazilian	Pre-war	0	Maximum	1.38	0.11	−0.01
			Median	0.58	0.03	−0.05
			Minimum	−0.52	−0.06	−0.38
			Mean	0.57	0.03	−0.05
			Standard deviation	0.24	0.01	0.02
	During-war	82.91	Maximum	0.76	0.02	0.04
			Median	−0.07	0.00	0.02
			Minimum	−2.34	−0.13	−0.03
			Mean	−0.31	−0.01	0.02
			Standard deviation	0.71	0.02	0.02

Source(s): Prepared by the authors

Table 2. Profitability and maximum transaction costs for the machine learning models

5. Conclusion and remarks

This paper analyzed the effectiveness of SVMs for stock price movement directions for three financial markets from a comparative perspective between the performances before and after the deflagration of the 2022 Russia–Ukraine war. The merits of the application of machine learning methods in recent research on empirical finance were also discussed, as well as the background for the conflict and its relevance to the global economy.

Different settings of hyperparameters were tested in an extensive grid search, applying 10-fold cross-validation for the training set and evaluating the classification performance and strategies' profitability for two mutually exclusive sets of out-of-sample data, investigating the overall impacts of hyperparameter settings on the predictive performance of the machine learning models. Results indicate that while the machine learning models did not manage to outperform the buy-and-hold strategy in terms of profitability for the pre-war period, the vast majority of the models were able to yield larger returns than the buy-and-hold benchmark during the period of war, which introduced a high amount of instability and volatility to the international market.

The findings of this research provide an assessment of the empirical challenges of machine learning applications to quantitative finance, while also adding to the literature of financial theory by exploring the connections between well-established concepts in finance and novel evidence brought by data science methods, notably during armed conflicts or other meaningful events with systemic implications. Moreover, the values for the transaction cost levels for an investor to reach some economic gain or to outperform the buy-and-hold strategy can be used to analyze the overall attractiveness of different financial markets, with an investor potentially willing to operate in markets in which the transaction costs are lower than the thresholds reported in this paper.

About the main limitations of this paper, the tested combinations of hyperparameters are not exhaustive, and the only predictive model employed in this paper used was the SVM with Gaussian Kernel, whereas there is a range of Kernels that can be applied with the same methodology that may lead to different results. In addition to combinations of other predictive methodologies such as ensemble-based models that can improve the predictive capacity of the strategies. Another relevant point is that the Russia–Ukraine war is still ongoing; therefore, the results presented here may not be maintained until the end of the conflict. Finally, the replication of the experiments of this paper for other periods of high market instability is encouraged, as well as for additional markets and independent variables, both for technical analysis indicators and fundamentalist features.

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