

2025-03

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X. Zhang, E. Pinsky. 2025. "S&P-500 vs. Nasdaq-100 price movement prediction with LSTM for different daily periods" Machine Learning with Applications, Volume 19, pp.100617-100617. <https://doi.org/10.1016/j.mlwa.2024.100617>

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S&P-500 vs. Nasdaq-100 price movement prediction with LSTM for different daily periods

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ARTICLE INFO

Dataset link: https://github.com/XiangZhang-z/x/SP_Nasdaq_Price_Movement_Prediction

Keywords:

LSTM
Price movement prediction
Stock market forecasting
Deep learning
Time series analysis
Trading strategies

ABSTRACT

This paper explores the efficiency of LSTM neural networks in predicting price movements for the two major U.S. stock indices: the S&P-500 and the Nasdaq-100 index. We consider three distinct daily periods: “overnight” (Close-to-Open), “daytime” (Open-to-Close) and “24-hour” (Close-to-Close) trading sessions. Using historical pricing data for these indices since 2000, this study shows how well the standard LSTM model captures price movement patterns to improve short-term trading strategies. The findings reveal that, for the S&P-500, a one-year training with 24-hour periods delivers a 14.5% more return over the Buy-and-Hold strategy. Moreover, combining “overnight” and “daytime” strategies delivers more than 40% return compared to passive index investing. By contrast, for the Nasdaq-100, a shorter training period of three months for “24-hour” periods delivers 90% more return than passive index investing. These results suggest that LSTM effectively learns the unique market dynamics associated with each index and different time periods, offering further insights into how deep learning can enhance financial forecasting and trading opportunities.

1. Introduction

Predicting price movements in stock markets has been a challenging problem for both academicians and practitioners. The inherent volatility and the stochastic nature of the markets makes price predictions and consistent profitable trading strategies difficult to realize in practice. Not surprisingly, machine learning solutions have been suggested to deal with this difficulty. These include LSTM (Long Short Term Memory) models, a class of artificial neural networks meant to deal with sequence problems, as an effective tool in financial forecasting. Specifically, the uniqueness of LSTM lies in its ability to model long-term dependencies, which is critical in the analysis of financial time series data. This enables them to retain information for a very long time and thus helps discover patterns and tendencies—an advantage in predicting stock market movements.

The paper presents a comparison of predicting price movements for different periods using LSTM. We chose two indices to assess how well LSTM models predict the movements: the S&P-500 and the Nasdaq-100 index. The S&P-500 is a market-capitalization index of the largest 500 companies. The Nasdaq-100 is the more narrow index, focusing on the largest technology companies. The Nasdaq-100 is historically more volatile. Both indices are widely used as benchmarks for many mutual funds and trading strategies. The exchange-traded funds (ETFs) for these indexes, ‘SPY’ for S&P-500 and ‘QQQ’ for Nasdaq-100, are

among the most liquid instruments and can be used to trade with minimal trading costs and slippage.

Although LSTM was introduced more than 20 years ago, we chose this early neural network architecture to see if it is capable of predicting price movements for these indices and offering a profitable trading strategy. Our results show that these early deep-learning networks can be used to predict price movements for major stock indices like the S&P-500 and Nasdaq-100. We focus on three trading periods: “overnight”, “daily”, and “24-h” sessions. The goal is to compare short-term trading strategies by using LSTM models to capture price movement patterns. Our results suggest that LSTM can generate better returns compared to passive (Buy-and-Hold or B&H) investing strategies.

2. Methodology and innovation

The accurate prediction of stock prices has been a focused area in financial research, where fundamental, technical analysis and statistical models are used. However, these traditional methods are often challenged by their inability to capture the complex non-linear relationships inherent in financial time-series data.

The emergence of deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, has significantly advanced market prediction research (Ahmed et al., 2022; Chen et al., 2023; Huang

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& Yen, 2019; Johari & Ahmed, 2021; Lara-Benítez et al., 2021; Nguyen & Ślepaczuk, 2022; Shukla et al., 2023; Yu et al., 2019). Introduced by Hochreiter and Schmidhuber in 1997 (Hochreiter & Schmidhuber, 1997), LSTMs excel in capturing complex, non-linear relationships in financial time-series data and have been applied to tasks like stock forecasting (Althelaya et al., 2018), portfolio optimization (Aldridge & Avellaneda, 2019), sentiment analysis (Huang & Yen, 2019), and risk assessment (Coats & Fant, 2013). Recent studies focus on enhancing accuracy in market predictions (Rokhsatyazdi & Zainal, 2020) and trend forecasting, such as predicting S&P 500 movements (Fischer & Krauss, 2017). While much research evaluates LSTM’s general predictive accuracy, this work uniquely analyzes its performance in predicting returns across distinct trading periods (overnight, daytime, and 24-h), emphasizing its relevance for short-term trading strategies. For detailed bibliographic references, see Althelaya et al. (2018), Fischer and Krauss (2017), and Rokhsatyazdi and Zainal (2020).

This paper focuses on the following questions:

- Can LSTM predict and capture price movement data in different day periods (overnight, daily, or 24-h) so that a profitable short-term strategy can be devised?
- Can we use well-known time-series data to help us understand the limitations of LSTM performance?

We consider two widely used trading exchange-traded funds (ETFs), “SPY” and “QQQ”, that are proxies for the S&P-500 and Nasdaq Composite Index, respectively. We consider 3 time periods for each day (“overnight”, “daytime” and 24-h). For each time period, we train LSTM and predict price movements one period at a time. We show that LSTM could offer predictions for a profitable trading strategy and we compare the results for S&P-500 and Nasdaq-100 for different daily time periods.

This paper is organized as follows: In Section 2, we outline the methodology, including data collection, preprocessing, and feature engineering. In Section 3, we detail the LSTM model and its application. In Section 4, we present the results for S&P and Nasdaq. In Appendices A and B, we provide detailed annual tables for the proposed strategies. Finally, in Appendix C we provide details on hyperparameter tuning.

In this paper, we focus on the two widely used indices S&P-500 and Nasdaq-100. Both indices are market-capitalization indices. The S&P-500 contains the largest 500 companies (market capitalization) and is often used as a benchmark for the overall stock market whereas the Nasdaq-100 contains major high-technology companies. We selected the S&P-500 and Nasdaq-100 indices over the S&P-100 index and the Nasdaq Composite index, respectively, because the S&P-500 and Nasdaq-100 are the most widely used indices for trading and investing.

2.1. Innovation in approach

Unlike previous studies that apply LSTM primarily to direct price prediction or general market trends, we evaluate LSTM performance across three distinct trading periods: overnight, daytime, and 24-h cycles. Our methodology evaluates the performance of LSTM in two ways:

1. From a machine learning perspective, by assessing how well the model recovers patterns in different return types and timelines.
2. From a trading perspective, by analyzing the profitability and practical utility of trading strategies informed by LSTM predictions.

This dual evaluation approach ensures the model is both technically accurate and practically valuable for financial decision-making. The methodology can be extended to other neural network architectures.

Table 1
Example of historical stock data.

Date	Open	Close
03/10/99	128	129
03/11/99	130	131
03/12/99	131	129
03/15/99	130	131
...

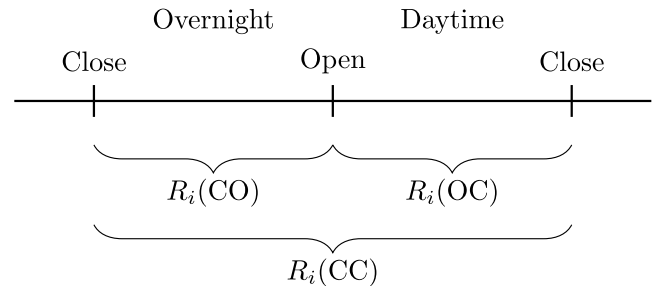


Fig. 1. CO, OC, and CC returns over a 24-h period.

Table 2
Example of historical stock data with returns.

Date d_i	Open	Close	$R_i(CC)$	$R_i(CO)$	$R_i(OC)$
03/10/99	128	129	0.00	0.39	0.56
03/11/99	130	131	1.11	0.29	0.72
03/12/99	131	129	-0.96	0.43	-1.24
03/15/99	130	131	1.43	-0.07	0.99

2.2. Data collection and pre-processing

Historical stock data for the S&P-500 and Nasdaq-100 index were collected from Yahoo Finance using the ‘yfinance’ library, covering the period from March 10, 1999, to June 30, 2024. The data pre-processing included calculating daily returns and labeling them as ‘+’ for positive returns and ‘-’ for negative returns.

Table 1 provides an example of the daily S&P open and close prices (see Fig. 1).

We divide each day d_i into three time periods and compute the corresponding returns as follows:

1. CC (Close-to-Close or “24-h” trading): the return is computed as the percent change between the Close price of trading day d_{i-1} and Close price of the day d_i . We will use the notation $R_i(CC)$ to denote such returns. For example, the $R_i(CC)$ return for S&P between $d_{i-1} = 03/12/99$ and $d_i = 03/15/99$ is $R_i(CC) = (131 - 129)/129 = 1.43\%$.
2. CO (Close-to-Open or “overnight” trading): the return is computed as the percent change between the Close price at d_i and Open price at d_{i+1} . We will use the notation $R_i(CO)$ to denote such returns. For example, the $R_i(CO)$ return for S&P between $d_i = 03/12/99$ and $d_{i+1} = 03/15/99$ is $R_i(CO) = (130 - 129)/129 = 0.43\%$.
3. OC (Close-to-Open or “daytime” trading): the return is computed as the percent change between the Open and Close prices at d_i . We will use the notation $R_i(OC)$ to denote such returns. For example, the $R_i(OC)$ return for S&P for $d_i = 03/12/99$ is $R_i(OC) = (129 - 131)/129 = -1.24\%$.

From the initial Close and Open price data in Table 1, we compute the returns data for the three periods. An example is given in Table 2.

2.3. Feature engineering

Features were engineered to encapsulate market dynamics, including generating return label sequences to capture short-term market

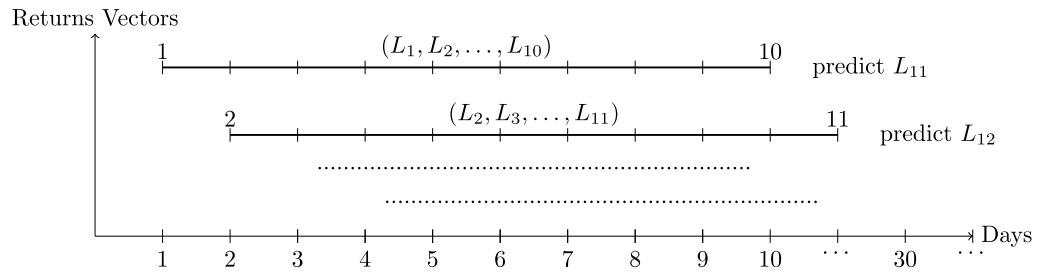


Fig. 2. Illustration of the sliding window ($W = 10$) prediction of return vectors over time.

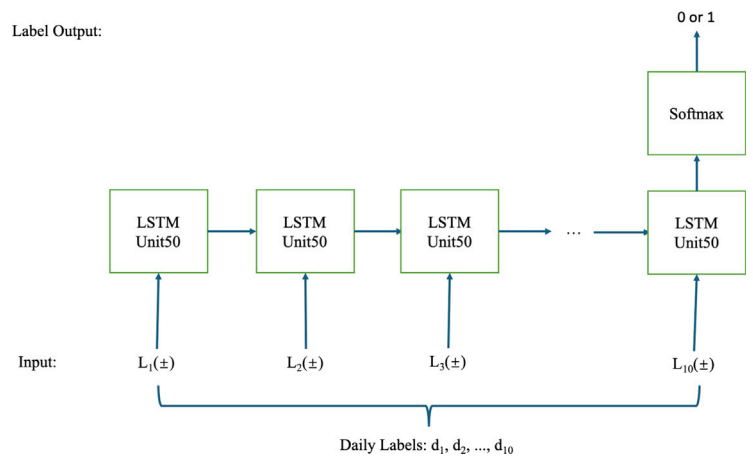


Fig. 3. Example LSTM model architecture with $W = 10$.

trends. We use the window size of $W = 10$ trading days to generate such sequences. This is a common window size in many technical trading algorithms (Edwards et al., 2002). In Section 4.3, we considered other window sizes but found that they do not affect the performance of LSTM.

We mapped the returns $(r_1, r_2, \dots, r_{10})$ to binary labels $(L_1, L_2, \dots, L_{10})$, with positive returns as “+” and non-positive returns as “-”. Each 10-period sequence was used to predict the labels for the next period. For example, $(L_1, L_2, \dots, L_{10})$ predicts the label on the 11th period, and $(L_2, L_3, \dots, L_{11})$ predicts the 12th period and so on (see Fig. 2).

$$\text{Label } L_i = \begin{cases} + & \text{if } r_i > 0 \\ - & \text{if } r_i \leq 0 \end{cases}$$

Below is a graphical representation of the return labels:

3. LSTM network for price movement prediction

Our LSTM model for price movement prediction is a standard LSTM model. For this model, we take window size $W = 10$, epochs $E = 10$, and standard LSTM unit 50. It is illustrated in Fig. 3.

The model consists of the following two layers:

- LSTM Layer:** An LSTM layer with 50 units. It captures temporal dependencies. It means the LSTM will output 50-dimensional vector at each time step. The input shape is $(\text{max_length}, 1)$, where max_length denoted as W is the sequence length (window), with $W = 10$.
- Dense Layer:** A dense layer with 2 units and a standard “SofM-max” activation function. It outputs the prediction probabilities for two classes: 0 for cash and 1 for investing in S&P or Nasdaq.

For example, from Table 2, the labels for overnight returns $R_i(\text{OC})$ for 03/10/99 to 03/15/99 are $\{+, +, -, +\}$ whereas the labels for 24-h returns $R_i(\text{CC})$ are $\{-, +-, +\}$. We provide vectors of such returns of length $W = 10$ as input to LSTM. The value W and E are hyperparameters. We initially chose the window size to correspond to 2 weeks ($W = 10$ trading days) and the number of epochs $E = 10$. This is a common value used in many algorithms (Edwards et al., 2002). We investigate these hyperparameters in more detail in Section 4.3. The details for LSTM are presented in Appendix D.

4. Results

For both S&P-500 and Nasdaq-100 (NDX), we compute the balance growth (starting with \$100 in 1999) using returns of different daily periods. We compute the final balances for different time and training periods as well as the final balances in passive index investing (“Buy-and-Hold” or B&H strategy). The results are shown in Table 3.

Appendix A contains detailed tables for SPY (Table A.1–Table A.9). The tables are presented in the following Appendices:

- Table A.1: SPY and NDX Transition Summary
- Table A.2: SPY Return Summary
- Table A.3: NDX Return Summary
- Table A.4: Transaction Number
- Table A.5: Annual Balance for S&P LSTM Strategies
- Table A.6: Annual Return for S&P LSTM Strategies
- Table A.7: Annual Maximum Drawdown for S&P LSTM Strategies
- Table A.8: Annual Volatility for S&P LSTM Strategies
- Table A.9: Annual Sharp Ratio for S&P LSTM Strategies

Appendix B contains detailed tables for NDX (Table B.1–Table B.5). The tables are presented as follows:

- Table B.1: Annual Balance for Nasdaq-100 LSTM Strategies
- Table B.2: Annual Return for Nasdaq-100 LSTM Strategies

Table 3
Summary of S&P and Nasdaq combined end balance.

Stock	B&H	LSTM strategies training period								
		1Y			6M			3M		
		CO	CC	OC	CO	CC	OC	CO	CC	OC
S&P	379	343	434	198	340	241	139	245	165	94
NDX	540	722	628	101	727	1024	77	1027	467	39

Table 4
Median accuracy summary of S&P and Nasdaq LSTM strategies.

Period	LSTM strategies								
	1Y			6M			3M		
	CO	CC	OC	CO	CC	OC	CO	CC	OC
S&P	52.8	53.8	52.9	52.4	52.8	52.4	52.8	52.9	50.0
NDX	53.9	52.8	51.6	53.6	53.8	51.6	54.4	52.2	50.6

Table A.1
SPY and NDX transition summary.

Year	S&P						NDX					
	CO		CC		OC		CO		CC		OC	
	\	/	\	/	\	/	\	/	\	/	\	/
2000	70	70	61	60	62	61	69	69	65	65	64	64
2001	69	69	63	63	65	65	62	62	64	64	68	68
2002	76	76	71	72	64	65	75	75	65	65	62	62
2003	72	72	65	65	71	71	71	71	70	70	70	70
2004	66	66	62	61	64	63	70	70	63	63	64	64
2005	64	64	68	68	69	69	59	59	63	63	58	58
2006	70	70	59	59	65	65	63	63	60	61	63	63
2007	75	75	71	71	65	65	71	71	64	63	60	60
2008	67	67	62	63	66	67	66	66	67	68	68	69
2009	71	71	62	61	59	58	74	74	62	61	57	56
2010	66	66	63	64	64	65	70	70	57	57	62	62
2011	69	69	62	61	59	58	67	67	61	61	57	57
2012	67	67	57	58	69	70	66	66	55	56	63	64
2013	62	61	64	64	60	60	61	60	65	65	65	65
2014	67	68	67	66	59	58	64	65	66	65	63	62
2015	70	69	66	66	67	67	68	67	58	58	62	62
2016	60	61	74	74	68	68	63	64	68	68	75	75
2017	63	63	67	67	61	61	65	65	64	64	61	61
2018	66	65	58	59	56	57	70	69	66	67	60	60
2019	64	65	58	58	61	61	61	62	58	58	64	65
2020	72	72	72	72	72	72	66	66	67	67	71	71
2021	62	62	64	63	65	64	65	65	63	62	62	61
2022	68	68	62	62	60	61	65	65	63	63	61	62
2023	66	65	63	63	62	61	60	59	59	59	64	63
2024	29	29	26	26	32	32	33	33	27	27	28	28
max	76	76	74	74	72	72	75	75	70	70	75	75
min	29	29	26	26	32	32	33	33	27	27	28	28
M	67	67	63	63	64	64	66	66	63	63	63	62
μ	66	66	63	63	63	63	65	65	62	62	62	62
σ	9	9	9	9	8	8	8	8	8	8	8	8

- Table B.3: Annual Maximum Drawdown for Nasdaq-100 LSTM Strategies
- Table B.4: Annual Volatility for Nasdaq-100 LSTM Strategies
- Table B.5: Annual Sharp Ratio for Nasdaq-100 LSTM Strategies

From Table 3, we see that for the S&P-500, the 24-h period with one year of training data yields the best result. The final balance was \$434, a 14.5% improvement over the Buy-and-Hold (B&H) strategy at \$379. Using a combined “overnight” CO (Close-to-Open) and “daytime” OC (open-to-close) strategy further increases the balance to \$680, nearly doubling the B&H result. For the Nasdaq-100, a 3-month “overnight” CO strategy achieved a final balance of \$1027, almost twice the B&H performance of \$540.

In Table 4 we compare the accuracy of LSTM for different time periods.

From Table 4, we can see that for S&P-500, the accuracy is highest for 1 year of training data on the “24-h” CC strategy and is 53.8%. In other words, for S&P, which has lower volatility than Nasdaq, the

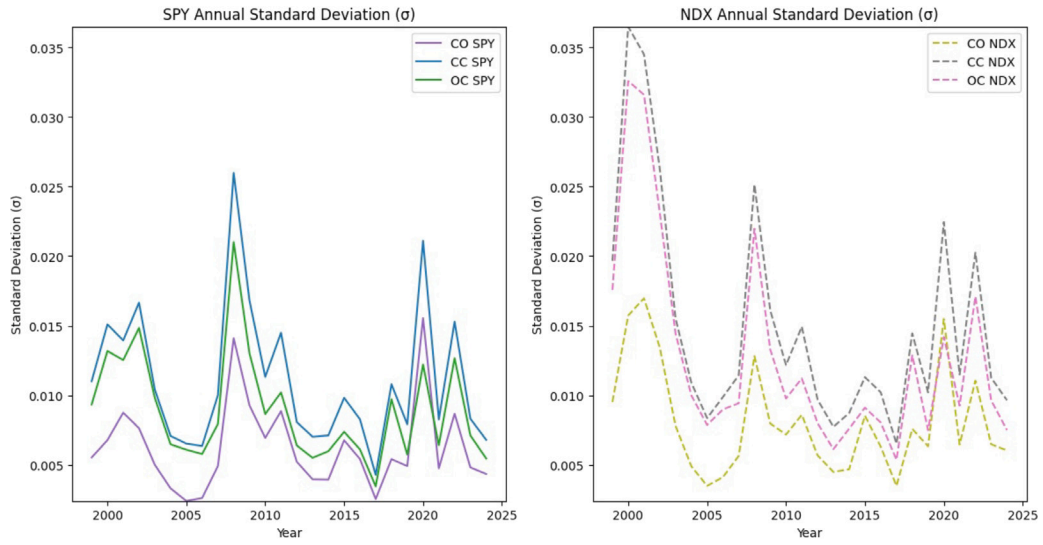


Fig. 4. Volatility returns for different time periods.

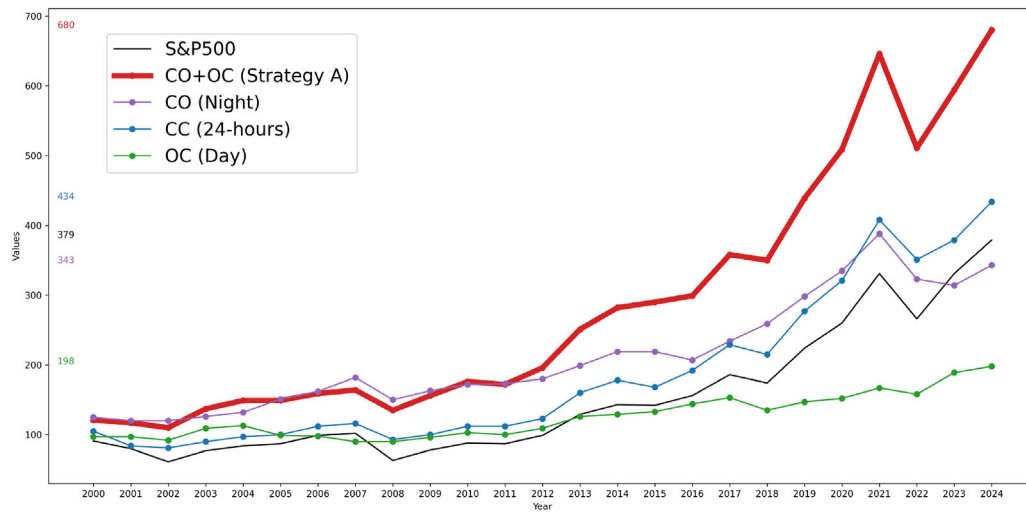


Fig. 5. End balance comparison for CO+OC combined strategy, CO, OC, CC, and S&P-500 (1 yr training period).

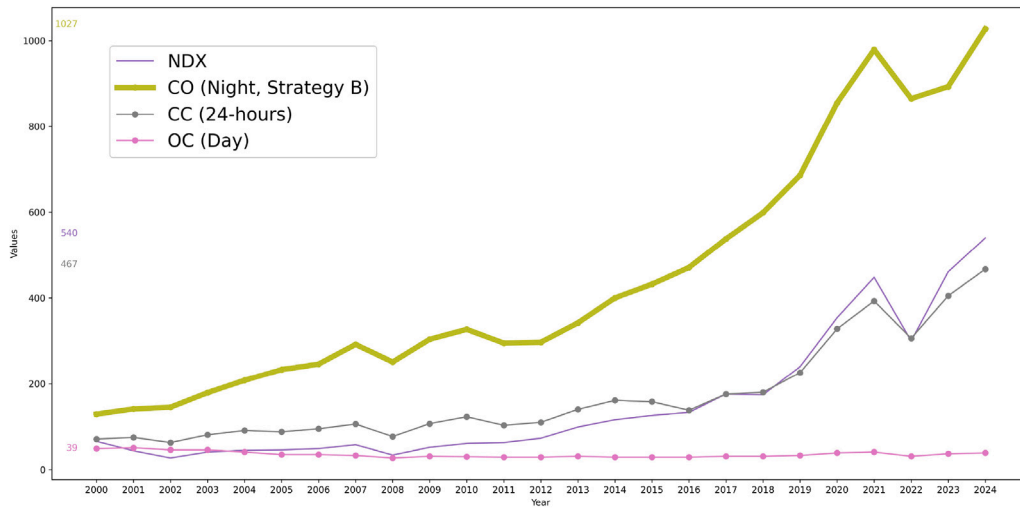


Fig. 6. End balance comparison for CO, OC, CC, and Nasdaq (6 months training period).

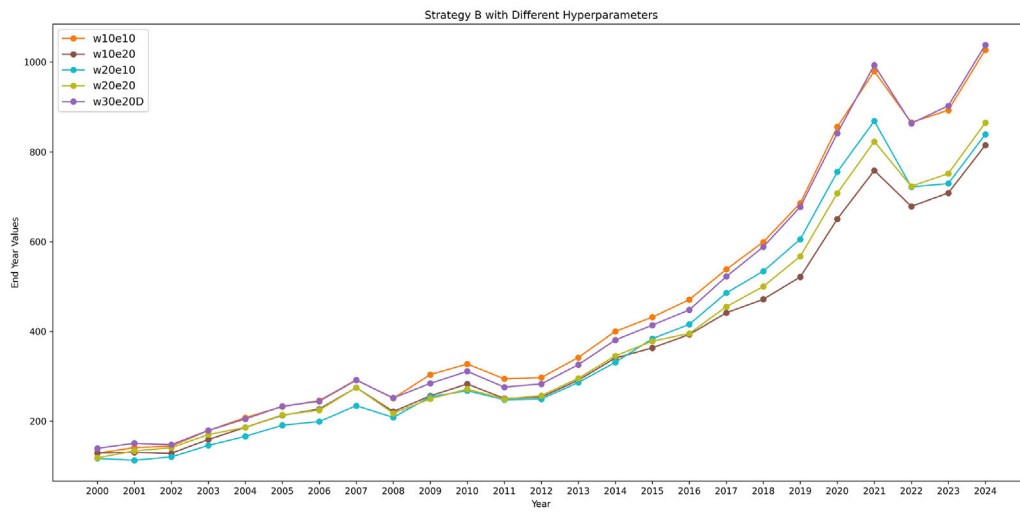
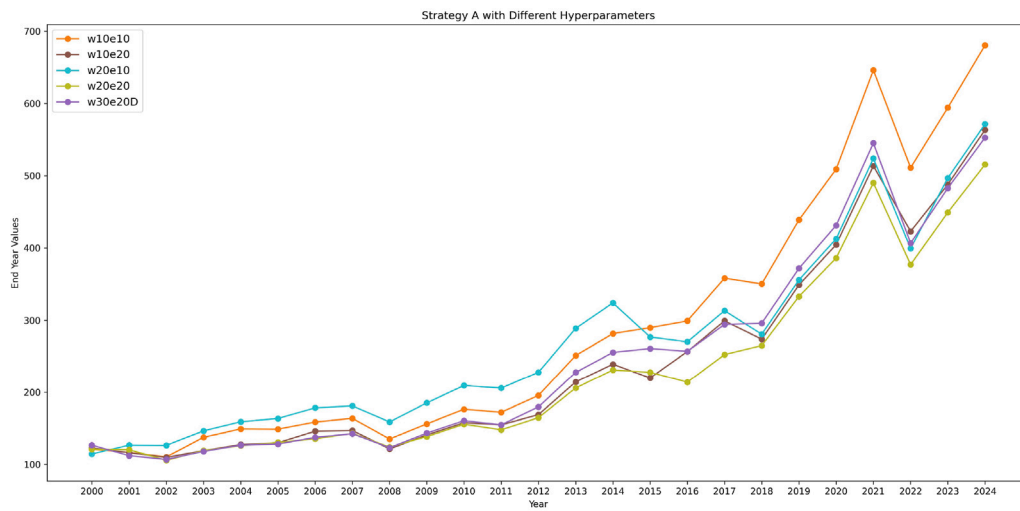


Fig. 7. Different hyperparameters.

Table A.2
S&P return summary.

Year	CO				CC				OC			
	T^+	T^-	r^+	r^-	T^+	T^-	r^+	r^-	T^+	T^-	r^+	r^-
2000	138	110	0.53	-0.45	122	130	1.16	-1.15	112	139	1.01	-1.04
2001	116	129	0.49	-0.56	124	124	1.02	-1.11	125	121	0.97	-0.97
2002	120	130	0.56	-0.60	119	133	1.26	-1.30	122	130	1.13	-1.15
2003	142	107	0.34	-0.41	142	108	0.81	-0.83	134	117	0.79	-0.74
2004	131	120	0.27	-0.25	140	109	0.53	-0.60	141	108	0.46	-0.56
2005	147	105	0.21	-0.17	136	113	0.49	-0.56	121	130	0.46	-0.50
2006	128	115	0.23	-0.19	138	113	0.48	-0.47	142	105	0.40	-0.50
2007	139	108	0.37	-0.36	137	113	0.67	-0.78	126	123	0.54	-0.63
2008	130	122	0.84	-1.01	126	127	1.55	-1.85	115	136	1.48	-1.44
2009	140	112	0.66	-0.77	139	113	1.18	-1.23	139	110	0.91	-0.98
2010	132	119	0.50	-0.51	143	108	0.75	-0.87	142	108	0.60	-0.72
2011	129	121	0.62	-0.63	133	119	0.98	-1.08	135	116	0.68	-0.81
2012	131	119	0.38	-0.39	136	112	0.60	-0.61	135	112	0.48	-0.49
2013	139	111	0.30	-0.29	145	104	0.56	-0.53	153	99	0.39	-0.44
2014	143	107	0.28	-0.29	147	105	0.49	-0.58	140	111	0.40	-0.48
2015	124	127	0.42	-0.42	121	131	0.75	-0.69	125	124	0.54	-0.54
2016	129	113	0.34	-0.41	136	115	0.58	-0.60	139	112	0.46	-0.43
2017	142	96	0.22	-0.20	141	109	0.34	-0.27	134	113	0.25	-0.24
2018	140	111	0.40	-0.41	132	117	0.69	-0.82	127	122	0.57	-0.74
2019	148	103	0.36	-0.38	149	103	0.57	-0.57	138	112	0.43	-0.40
2020	144	109	0.84	-0.98	146	107	1.23	-1.48	147	105	0.74	-0.99
2021	154	98	0.35	-0.39	146	106	0.63	-0.64	137	114	0.48	-0.50
2022	114	137	0.65	-0.65	108	142	1.31	-1.13	127	124	0.98	-1.03
2023	127	122	0.38	-0.37	140	109	0.66	-0.65	147	103	0.53	-0.58
2024	77	45	0.33	-0.35	71	53	0.56	-0.49	67	57	0.41	-0.39
max	154	137	0.84	-0.17	149	142	1.55	-0.27	153	139	1.48	-0.24
min	77	45	0.21	-1.01	71	53	0.34	-1.85	67	57	0.25	-1.44
M	132	112	0.38	-0.41	137	113	0.67	-0.69	135	113	0.54	-0.58
μ	132	112	0.43	-0.46	133	113	0.79	-0.83	131	114	0.64	-0.69
σ	15	17	0.18	0.22	16	16	0.32	0.37	17	16	0.29	0.29

Table A.3
NDX return summary.

Year	CO				CC				OC			
	T^+	T^-	r^+	r^-	T^+	T^-	r^+	r^-	T^+	T^-	r^+	r^-
2000	136	113	1.19	-1.12	122	126	2.82	-2.96	123	125	2.30	-2.81
2001	118	127	1.29	-1.21	123	122	2.53	-2.77	120	127	2.26	-2.31
2002	113	138	1.10	-1.01	117	134	2.13	-2.14	113	138	2.01	-1.82
2003	145	104	0.57	-0.58	142	109	1.23	-1.21	140	112	1.08	-1.18
2004	136	114	0.41	-0.37	131	119	0.87	-0.87	130	118	0.73	-0.84
2005	144	98	0.29	-0.27	133	116	0.64	-0.72	116	134	0.62	-0.64
2006	135	110	0.32	-0.33	137	113	0.73	-0.81	134	110	0.66	-0.80
2007	139	109	0.44	-0.39	144	105	0.83	-0.96	127	119	0.70	-0.75
2008	131	117	0.76	-0.98	112	139	1.78	-1.77	121	129	1.55	-1.69
2009	136	114	0.62	-0.62	149	101	1.15	-1.24	142	109	0.98	-0.97
2010	138	109	0.52	-0.52	141	108	0.84	-0.92	130	121	0.74	-0.76
2011	126	123	0.62	-0.61	133	117	1.06	-1.16	131	121	0.85	-0.90
2012	137	111	0.42	-0.41	127	119	0.79	-0.70	139	108	0.56	-0.68
2013	150	95	0.33	-0.37	147	104	0.61	-0.57	135	110	0.48	-0.46
2014	149	100	0.34	-0.35	145	105	0.63	-0.70	138	111	0.52	-0.62
2015	134	114	0.49	-0.50	131	120	0.82	-0.82	130	120	0.63	-0.69
2016	136	113	0.39	-0.45	132	118	0.72	-0.74	132	119	0.58	-0.58
2017	148	102	0.29	-0.24	155	96	0.47	-0.46	146	104	0.36	-0.41
2018	139	109	0.55	-0.59	136	115	0.96	-1.12	128	121	0.83	-0.98
2019	150	100	0.46	-0.52	149	103	0.75	-0.76	134	117	0.59	-0.51
2020	157	96	0.85	-1.12	158	95	1.35	-1.76	145	107	0.98	-1.16
2021	146	106	0.47	-0.50	143	108	0.86	-0.90	143	109	0.68	-0.79
2022	112	138	0.82	-0.82	111	140	1.67	-1.58	120	131	1.39	-1.37
2023	129	121	0.51	-0.47	141	109	0.95	-0.82	148	102	0.76	-0.77
2024	76	46	0.47	-0.47	71	53	0.77	-0.73	61	63	0.60	-0.54
max	157	138	1.29	-0.24	158	140	2.82	-0.46	148	138	2.30	-0.41
min	76	46	0.29	-1.21	71	53	0.47	-2.96	61	63	0.36	-2.81
M	136	110	0.49	-0.50	136	113	0.86	-0.90	131	118	0.73	-0.79
μ	134	109	0.58	-0.59	133	112	1.12	-1.17	129	115	0.94	-1.00
σ	17	17	0.28	0.28	18	17	0.61	0.65	17	14	0.54	0.59

Table A.4
Transaction number.

Year	A	MC-CC	MC-CO	MC-OC	QQ-CO
2000	493	82	1	8	22
2001	367	73	23	31	8
2002	238	35	50	39	18
2003	203	23	27	53	29
2004	2	0	2	0	36
2005	72	0	10	23	26
2006	186	4	6	75	36
2007	58	0	34	12	12
2008	476	63	12	13	31
2009	188	35	48	25	39
2010	2	0	2	0	32
2011	14	2	14	0	49
2012	64	6	54	4	37
2013	6	0	6	0	4
2014	0	0	0	0	6
2015	106	33	58	40	32
2016	307	47	83	32	18
2017	83	0	35	6	18
2018	82	0	0	46	15
2019	78	0	0	54	11
2020	0	0	0	0	0
2021	0	0	0	0	6
2022	105	19	15	6	25
2023	455	33	21	8	25
2024*	10	0	10	0	0
max	493	82	83	75	49
min	0	0	0	0	0
M	82	2	12	8	22
μ	144	18	20	19	21
σ	160	25	23	22	13

Table A.5
Annual balance for S&P LSTM strategies.

Year	B&H S&P	Training period								
		1Y			6M			3M		
		CO	CC	OC	CO	CC	OC	CO	CC	OC
2000	91	125	105	97	124	91	97	121	82	83
2001	80	120	84	97	124	73	95	112	70	73
2002	61	120	81	92	119	72	88	110	68	64
2003	77	126	90	109	127	79	87	121	81	77
2004	84	132	97	113	131	87	89	128	91	78
2005	87	151	100	99	147	88	83	142	90	74
2006	99	162	112	98	156	97	80	150	92	75
2007	102	182	116	90	176	103	77	171	97	75
2008	63	150	93	90	149	60	76	132	60	74
2009	78	163	100	96	160	63	88	155	60	86
2010	88	172	112	103	153	66	90	152	62	85
2011	87	173	112	100	152	64	80	138	68	68
2012	99	180	123	109	149	70	88	133	72	70
2013	129	199	160	126	161	90	102	139	88	81
2014	143	219	178	129	173	100	104	150	96	79
2015	142	219	168	133	173	100	103	146	95	79
2016	156	207	192	144	169	110	122	148	102	87
2017	186	234	229	153	190	131	129	160	118	90
2018	174	259	215	135	210	115	104	177	121	86
2019	224	298	277	147	239	148	113	198	148	93
2020	260	335	321	152	268	172	117	207	128	97
2021	331	388	408	167	311	218	126	239	162	106
2022	266	323	351	158	295	190	125	213	137	89
2023	331	314	379	189	307	210	133	223	150	94
2024 ^a	379	343	434	198	340	241	139	245	165	94

^a Data for 2024 is up to June 30, 2024.

LSTM model requires longer training. In the case of Nasdaq-100, the maximum accuracy reaches 54.4% for a 3-month training period with the “overnight” returns strategy. This means that the more volatile Nasdaq-100 index requires shorter training periods necessary to yield a very profitable trading strategy.

For the S&P-500, one year of training is required, especially for the CC strategy, which shows consistent improvement. By contrast, for Nasdaq-100, a shorter training period is sufficient. With 3 months of training, the CO strategy outperforms B&H and nearly doubles the final balance. This suggests that short-term modeling is more effective for Nasdaq-100 due to its dynamic nature. If we consider combining “overnight” and “daytime” strategies, then we can almost double the results. The results are shown in Fig. 5. By contrast, for Nasdaq-100, the best training period is 3-month using an “overnight” CO periods. We note that with 3-month training, the “daytime” OC strategy yields negligible returns. The results are shown in Fig. 6.

One plausible explanation for this difference in shorter training periods for Nasdaq-100 is its higher volatility. In Fig. 4 we compare annual standard deviations of returns for the three time periods (overnight, daytime, and 24-h) for S&P-500 and Nasdaq-100. It is evident that S&P-500 volatility is relatively lower compared to that of Nasdaq-100. Therefore, when we use LSTM to predict S&P-500 price movements, training with one year of data yields better results, while just three months of training data is enough for Nasdaq-100.

4.1. Results and analysis of S&P-500 predictions using LSTM

The performance of LSTM for predicting S&P-500 price movements has been analyzed, focusing on trading strategies across overnight, daytime, and 24-h periods. Key results indicate that a one-year training period outperforms shorter periods for stable market indices like the S&P-500. Detailed results, including annual balances and volatility analysis, are provided in Appendix E.

4.2. Results and analysis of Nasdaq-100 predictions using LSTM

For the Nasdaq-100, a more volatile index, shorter training periods (e.g., three months) yield better results. This demonstrates the adaptability of LSTM to dynamic market conditions. Detailed results, including performance metrics, are provided in Appendix F.

4.3. Hyperparameter tuning

In specifying the LSTM, there are three hyper-parameters that could directly affect the performance of the underlying trading strategies:

1. the use of dropout layers
2. LSTM layer size
3. number of epochs E and window size W (maximum number of data)

Our initial configuration was $W = 10$ and $E = 10$ with a dropout layer 0.2. We considered the following alternative values for hyperparameters as follows:

1. for a fixed value of $W = 10$, we double the number of epochs from $E = 10$ to $E = 20$ — we call this a $w10e20$ configuration
2. we double the window size to $W = 20$ days and consider $E = 10$ and $E = 20$ epochs — we call these $w20e10$ and $w20e20$ configurations respectively
3. we triple the window size to $W = 30$, double the number of epochs to $E = 20$, and add a dropout layer of 0.2 and an additional LSTM layer with 50 units — we call this a $W30E20D$ configuration.

We found that these configurations have negligible effect on the execution time. All of these modifications add to the complexity of the underlying LSTM architectures. However, the effect of these changes on the growth of balances for both strategies A and B is not significant as shown in Fig. 7. The graphs show minimal changes to both strategies, especially for B . Similar results hold for other performance measures such as maximum drawdowns, volatility, and Sharp ratios.

Table A.6
Annual return for S&P LSTM strategies.

Year	B&H		Training period								
	S&P	A	1Y			6M			3M		
			CO	CC	OC	CO	CC	OC	CO	CC	OC
2000	-30.4	25.1	26.7	5.7	-1.2	25.8	-9.5	-3.3	22.3	-17.4	-15.3
2001	-11.5	-3.4	-3.3	-20.5	-0.1	0.0	-19.4	-1.8	-7.0	-15.3	-12.5
2002	-23.7	-5.8	-0.2	-4.7	-5.6	-4.0	-1.4	-7.5	-2.1	-2.2	-12.1
2003	22.3	24.7	5.2	11.2	18.6	7.3	9.3	-4.0	9.7	16.1	16.2
2004	8.7	8.6	4.0	8.7	4.5	2.8	10.5	3.4	5.8	11.4	1.8
2005	3.5	0.6	14.1	3.5	-11.8	11.6	1.9	-6.0	11.3	-0.5	-4.2
2006	11.9	6.6	7.4	10.1	-0.7	6.3	7.9	-4.2	5.3	0.5	1.6
2007	3.5	4.0	12.5	3.5	-7.6	13.2	6.6	-2.2	14.0	5.3	0.8
2008	-37.7	-16.6	-17.3	-18.7	0.8	-15.7	-41.6	-1.8	-22.5	-37.9	-1.0
2009	20.0	15.6	8.2	6.9	6.8	8.0	1.6	15.2	17.0	0.8	15.9
2010	11.0	12.2	5.8	11.0	6.1	-4.1	3.5	1.6	-1.4	1.4	-2.3
2011	-1.2	-2.9	0.3	-1.7	-3.2	-1.2	-3.4	-11.5	-9.4	8.7	-19.4
2012	11.8	14.3	4.3	8.7	9.6	-1.4	7.0	11.0	-3.4	4.3	3.0
2013	26.6	27.7	11.0	26.6	15.1	7.5	25.6	14.8	4.1	18.9	14.0
2014	12.4	12.7	9.6	12.4	2.9	7.3	12.3	2.3	8.2	10.1	-1.4
2015	-0.8	4.0	0.7	-5.6	3.4	0.6	0.3	-0.4	-2.2	-1.7	1.1
2016	11.2	2.8	-5.5	14.5	8.8	-2.2	9.7	18.6	1.1	7.8	9.0
2017	18.6	19.6	13.1	18.6	5.8	12.1	18.6	5.3	7.8	15.0	4.1
2018	-7.1	-2.3	10.4	-7.1	-11.5	10.6	-12.6	-19.1	10.5	1.9	-5.3
2019	28.8	24.2	16.2	28.8	6.9	14.8	28.2	8.7	12.3	22.5	8.2
2020	15.1	16.9	13.5	15.1	2.9	13.5	15.1	2.6	5.8	-14.5	4.1
2021	28.9	29.5	16.2	28.9	11.5	16.2	28.9	9.8	15.4	28.9	11.4
2022	-20.1	-21.5	-17.1	-14.6	-5.3	-5.6	-13.5	-1.1	-11.0	-16.4	-16.4
2023	25.1	17.6	-2.7	8.1	20.9	4.4	10.8	6.7	4.5	9.6	5.7
2024*	33.5	33.0	21.1	33.5	9.8	22.7	33.5	9.8	22.7	23.4	-0.4
max	33.5	33.0	26.7	33.5	20.9	25.8	33.5	18.6	22.7	28.9	16.2
min	-37.7	-21.5	-17.3	-20.5	-11.8	-15.7	-41.6	-19.1	-22.5	-37.9	-19.4
M	11.2	12.2	7.4	8.7	3.4	7.3	7.0	1.6	5.8	4.3	1.1
μ	6.4	9.9	6.2	7.3	3.5	6.0	5.2	1.9	4.7	3.2	0.3
σ	19.2	14.1	10.5	14.2	8.4	9.4	16.6	8.8	10.6	15.1	9.8

A: Combine 1Y S&P CO-OC.

Table A.7
Annual maximum drawdown for S&P LSTM strategies.

Year	B&H		Training period								
	S&P	A	1Y			6M			3M		
			CO	CC	OC	CO	CC	OC	CO	CC	OC
2000	-12.4	-6.4	-6.0	-11.2	-2.7	-6.0	-20.7	-3.8	-6.0	-18.2	-16.4
2001	-29.5	-9.2	-7.6	-21.3	-3.0	-5.5	-27.1	-14.5	-7.1	-18.2	-17.0
2002	-33.6	-11.3	-7.3	-6.5	-6.5	-9.2	-3.4	-11.8	-6.7	-7.4	-15.8
2003	-13.7	-6.3	-2.2	-4.4	-6.9	-3.2	-16.0	-13.0	-3.0	-12.1	-6.6
2004	-8.2	-8.0	-4.2	-8.2	-10.6	-3.2	-6.7	-11.5	-2.9	-7.0	-12.9
2005	-7.3	-7.0	-1.4	-7.3	-11.7	-1.4	-7.3	-11.9	-1.4	-7.3	-8.3
2006	-7.6	-4.9	-1.9	-7.6	-8.9	-2.5	-7.7	-11.4	-2.3	-11.1	-8.0
2007	-9.9	-9.9	-3.0	-9.9	-12.8	-3.4	-9.2	-9.7	-2.9	-9.0	-4.9
2008	-47.9	-20.1	-20.8	-27.6	-2.5	-17.9	-43.1	-5.1	-22.6	-44.1	-3.8
2009	-27.1	-7.8	-7.8	-27.0	-6.3	-3.7	-24.4	-9.2	-7.9	-24.0	-8.6
2010	-16.1	-15.4	-7.4	-16.1	-14.7	-10.2	-16.1	-14.8	-7.4	-13.4	-13.4
2011	-19.4	-21.0	-13.4	-19.8	-13.7	-13.7	-14.2	-16.6	-12.5	-7.5	-23.9
2012	-9.7	-9.6	-7.5	-12.2	-9.5	-8.6	-9.0	-5.9	-8.6	-10.7	-6.9
2013	-6.0	-5.9	-3.0	-6.0	-5.1	-3.0	-6.0	-5.1	-3.2	-6.0	-6.1
2014	-7.7	-9.2	-4.3	-7.7	-6.7	-4.3	-7.7	-6.7	-4.3	-4.9	-7.2
2015	-12.3	-6.3	-4.6	-14.4	-7.1	-3.9	-4.5	-4.5	-5.6	-9.1	-4.5
2016	-9.2	-6.6	-6.8	-5.3	-6.6	-5.0	-6.0	-5.4	-5.2	-6.0	-5.8
2017	-3.0	-2.3	-1.9	-3.0	-4.0	-2.0	-3.0	-4.4	-2.0	-3.7	-4.5
2018	-20.2	-14.9	-3.9	-20.2	-17.6	-3.9	-21.1	-22.9	-3.9	-10.2	-11.7
2019	-6.6	-7.0	-8.1	-6.6	-7.7	-7.5	-6.6	-3.7	-8.1	-6.6	-6.3
2020	-34.1	-32.4	-29.4	-34.1	-10.8	-29.4	-34.1	-11.1	-29.4	-35.1	-10.4
2021	-5.4	-5.3	-2.8	-5.4	-5.8	-2.8	-5.4	-6.8	-2.8	-5.4	-5.1
2022	-25.4	-25.4	-18.7	-23.4	-13.4	-6.7	-13.5	-10.8	-10.9	-17.5	-22.0
2023	-10.3	-10.1	-2.8	-5.8	-9.6	-3.2	-10.3	-9.6	-2.7	-8.7	-9.6
2024*	-5.4	-5.0	-1.5	-5.4	-6.7	-1.5	-5.4	-6.7	-1.5	-5.4	-6.6
max	-47.9	-32.4	-29.4	-34.1	-17.6	-29.4	-43.1	-22.9	-29.4	-44.1	-23.9
min	-3.0	-2.3	-1.4	-3.0	-2.5	-1.4	-3.0	-3.7	-1.4	-3.7	-3.8
M	-10.3	-8.0	-4.6	-8.2	-7.1	-3.9	-9.0	-9.6	-5.2	-9.0	-8.0
μ	-15.5	-10.7	-7.1	-12.7	-8.4	-6.5	-13.1	-9.5	-6.8	-12.4	-9.9
σ	11.4	7.2	6.8	8.6	4.0	6.2	10.2	4.7	6.5	9.7	5.5

Table A.8
Annual volatility for S&P LSTM strategies.

Year	B&H		Training period								
	S&P	A	1Y			6M			3M		
			CO	CC	OC	CO	CC	OC	CO	CC	OC
2000	26.1	10.9	10.7	16.2	2.7	10.7	15.2	3.5	10.5	14.2	8.3
2001	22.1	9.8	8.4	11.0	4.8	4.7	14.5	11.3	3.8	13.1	12.2
2002	26.5	9.7	6.7	5.1	6.7	6.7	3.5	9.6	5.3	9.2	12.0
2003	16.3	12.6	3.9	10.4	12.2	5.2	14.1	12.6	6.0	13.9	10.5
2004	11.2	10.7	5.2	11.2	10.3	4.4	11.1	10.2	4.2	10.5	10.1
2005	10.4	8.9	3.8	10.4	9.0	3.7	10.3	8.7	3.7	9.2	7.0
2006	10.0	7.6	4.1	9.9	6.8	4.0	9.6	7.7	3.8	7.8	7.4
2007	15.9	13.7	7.2	15.9	12.5	7.2	15.5	10.5	7.3	12.6	7.7
2008	41.3	22.9	21.7	24.1	6.4	20.3	33.5	5.7	17.7	30.3	4.9
2009	26.6	16.2	13.2	25.8	9.4	9.3	20.5	12.6	12.4	20.7	15.8
2010	17.9	17.3	11.0	17.9	13.7	10.5	16.8	13.3	9.9	14.5	11.7
2011	23.0	21.7	13.9	23.0	16.2	12.5	17.3	13.5	11.1	14.6	13.0
2012	12.7	13.2	7.8	12.6	10.2	7.9	12.2	9.6	6.4	9.9	7.8
2013	10.9	10.3	6.2	10.9	8.7	6.2	10.9	8.7	5.6	10.4	8.7
2014	11.3	11.6	6.2	11.3	9.5	6.1	11.3	9.5	6.0	10.1	8.2
2015	15.6	11.9	7.5	13.0	9.5	5.3	7.9	6.9	6.1	8.5	8.4
2016	13.1	9.0	3.2	8.8	8.5	6.0	9.1	9.0	6.5	9.2	7.3
2017	6.7	6.1	3.7	6.7	5.5	4.0	6.5	5.2	3.5	5.8	4.8
2018	17.2	15.6	8.6	17.2	13.6	8.6	16.3	12.9	7.5	12.9	8.0
2019	12.6	10.7	7.8	12.6	7.9	7.7	12.2	6.6	7.0	11.6	6.6
2020	33.6	29.4	24.7	33.6	19.4	24.7	33.6	19.4	24.2	29.1	19.4
2021	13.0	12.3	7.5	13.0	10.0	7.5	13.0	10.0	7.5	13.0	8.6
2022	24.3	22.8	11.5	18.9	20.1	8.0	11.0	17.7	7.2	6.8	16.4
2023	13.2	11.2	1.9	6.3	11.2	4.0	9.1	9.7	4.4	9.7	10.0
2024*	10.8	11.1	6.8	10.8	8.7	6.9	10.8	8.7	6.9	10.0	7.3
max	41.3	29.4	24.7	33.6	20.1	24.7	33.6	19.4	24.2	30.3	19.4
min	6.7	6.1	1.9	5.1	2.7	3.7	3.5	3.5	3.5	5.8	4.8
M	15.6	11.6	7.5	12.6	9.5	6.9	12.2	9.6	6.5	10.5	8.4
μ	17.7	13.5	8.5	14.3	10.1	8.1	13.8	10.1	7.8	12.7	9.7
σ	8.3	5.5	5.4	6.7	4.2	4.9	7.0	3.6	4.7	6.0	3.6

Table A.9
Annual sharp ratio for S&P LSTM strategies.

Year	B&H		Training period								
	S&P	A	1Y			6M			3M		
			CO	CC	OC	CO	CC	OC	CO	CC	OC
2000	-1.2	2.3	2.5	0.3	-0.5	2.4	-0.6	-0.9	2.1	-1.2	-1.8
2001	-0.5	-0.3	-0.4	-1.9	0.0	0.0	-1.3	-0.2	-1.9	-1.2	-1.0
2002	-0.9	-0.6	0.0	-0.9	-0.8	-0.6	-0.4	-0.8	-0.4	-0.2	-1.0
2003	1.4	2.0	1.3	1.1	1.5	1.4	0.7	-0.3	1.6	1.2	1.5
2004	0.8	0.8	0.8	0.8	0.4	0.6	0.9	0.3	1.4	1.1	0.2
2005	0.3	0.1	3.7	0.3	-1.3	3.1	0.2	-0.7	3.0	-0.1	-0.6
2006	1.2	0.9	1.8	1.0	-0.1	1.6	0.8	-0.5	1.4	0.1	0.2
2007	0.2	0.3	1.7	0.2	-0.6	1.8	0.4	-0.2	1.9	0.4	0.1
2008	-0.9	-0.7	-0.8	-0.8	0.1	-0.8	-1.2	-0.3	-1.3	-1.3	-0.2
2009	0.8	1.0	0.6	0.3	0.7	0.9	0.1	1.2	1.4	0.0	1.0
2010	0.6	0.7	0.5	0.6	0.4	-0.4	0.2	0.1	-0.1	0.1	-0.2
2011	-0.1	-0.1	0.0	-0.1	-0.2	-0.1	-0.2	-0.9	-0.9	0.6	-1.5
2012	0.9	1.1	0.5	0.7	0.9	-0.2	0.6	1.1	-0.5	0.4	0.4
2013	2.4	2.7	1.8	2.4	1.7	1.2	2.4	1.7	0.7	1.8	1.6
2014	1.1	1.1	1.5	1.1	0.3	1.2	1.1	0.2	1.4	1.0	-0.2
2015	0.0	0.3	0.1	-0.4	0.4	0.1	0.0	-0.1	-0.4	-0.2	0.1
2016	0.9	0.3	-1.7	1.7	1.0	-0.4	1.1	2.1	0.2	0.8	1.2
2017	2.8	3.2	3.6	2.8	1.1	3.0	2.8	1.0	2.2	2.6	0.9
2018	-0.4	-0.1	1.2	-0.4	-0.8	1.2	-0.8	-1.5	1.4	0.1	-0.7
2019	2.3	2.3	2.1	2.3	0.9	1.9	2.3	1.3	1.7	1.9	1.2
2020	0.4	0.6	0.5	0.4	0.2	0.5	0.4	0.1	0.2	-0.5	0.2
2021	2.2	2.4	2.2	2.2	1.1	2.2	2.2	1.0	2.1	2.2	1.3
2022	-0.8	-0.9	-1.5	-0.8	-0.3	-0.7	-1.2	-0.1	-1.5	-2.4	-1.0
2023	1.9	1.6	-1.4	1.3	1.9	1.1	1.2	0.7	1.0	1.0	0.6
2024*	3.1	3.0	3.1	3.1	1.1	3.3	3.1	1.1	3.3	2.4	-0.1
max	3.1	3.2	3.7	3.1	1.9	3.3	3.1	2.1	3.3	2.6	1.6
min	-1.2	-0.9	-1.7	-1.9	-1.3	-0.8	-1.3	-1.5	-1.9	-2.4	-1.8
M	0.8	0.8	0.8	0.6	0.4	1.1	0.4	0.1	1.4	0.4	0.1
μ	0.7	0.9	0.9	0.7	0.4	1.0	0.6	0.2	0.8	0.4	0.1
σ	1.2	1.2	1.5	1.2	0.8	1.2	1.2	0.9	1.4	1.2	0.9

Appendix C includes:

- [Table C.1](#): SPY-CO end balance and maximum drawdown
- [Table C.2](#): SPY-CC end balance and maximum drawdown
- [Table C.3](#): SPY-OC end balance and maximum drawdown
- [Table C.4](#): Nasdaq-CO end balance and maximum drawdown
- [Table C.5](#): Nasdaq-CC end balance and maximum drawdown
- [Table C.6](#): Nasdaq-OC end balance and maximum drawdown
- [Fig. C.1](#): S&P-CO different hyperparameters
- [Fig. C.2](#): S&P-CC different hyperparameters
- [Fig. C.3](#): S&P-OC different hyperparameters

5. Contributions and limitations

5.1. Novelty

The novelty of this paper lies in analyzing different time periods (“overnight”, “daytime”, and “24-h”) for the same securities and relating LSTM’s performance to the volatility and return characteristics of these periods. This approach identifies which time periods have patterns that LSTM can effectively recover, offering insights for short-term trading strategies.

5.2. Challenges overcome from previous works

Earlier studies struggled with LSTM overfitting and managing these indices’ different volatilities. This paper addresses these issues by setting a longer, one-year training period for the stable S&P-500 and a shorter, three-month period for the more volatile Nasdaq-100. This tailored approach reduces overfitting and allows faster, more accurate predictions, which is essential for high-frequency trading.

5.3. Limitations

This study has some limitations. It relies on past price patterns, which may not adapt well to sudden market changes or days with low trading volume. Also, the S&P-500 combined CO+OC strategy requires frequent trades, which could lead to high transaction costs that reduce net gains. Finally, while our models outperform Buy-and-Hold strategies, further research could compare LSTM performance against more complex trading algorithms.

6. Conclusion

In this paper, we applied LSTM for price movement predictions of two major US stock indices for different periods. Our results show that profitable trading strategies are possible even with these early deep-learning architectures. For the S&P 500, one year of training is needed to outperform B&H whereas for Nasdaq, shorter training periods of the 3-months is sufficient. Future research will focus on using other deep-learning architectures for price predictions and trading strategies.

Funding

This research was conducted without any external funding. All aspects of the study, including design, data collection, analysis, and interpretation, were carried out using the resources available within the authors’ institution.

Declaration of competing interest

The authors declare that there are no conflicts of interest related to this work.

Table B.1

Annual balance for Nasdaq-100 LSTM strategies.

Year	B&H	Training period									
		NDX	1Y			6M			3M		
			CO	CC	OC	CO	CC	OC	CO	CC	OC
2000	66	138	68	56	138	97	70	129	71	49	
2001	44	131	64	56	107	94	73	141	75	51	
2002	27	122	59	49	96	67	57	145	63	46	
2003	41	133	67	51	115	98	59	179	81	46	
2004	45	153	73	48	125	110	62	208	91	41	
2005	46	179	75	45	144	109	55	233	88	35	
2006	49	191	75	41	154	108	51	246	95	35	
2007	58	227	89	41	183	129	54	292	106	33	
2008	34	193	74	41	158	106	47	251	77	27	
2009	52	218	88	50	190	145	55	304	107	31	
2010	61	254	105	51	213	165	50	327	123	30	
2011	63	237	107	50	195	159	46	295	103	29	
2012	73	256	130	53	202	204	48	297	110	29	
2013	99	294	153	59	233	267	53	342	140	31	
2014	116	344	179	55	270	313	54	400	161	29	
2015	126	357	189	55	276	283	54	432	158	29	
2016	133	357	187	61	278	301	60	471	138	29	
2017	176	425	246	67	334	390	66	538	176	31	
2018	174	474	243	61	375	382	59	599	180	31	
2019	240	559	335	68	446	510	62	686	226	33	
2020	354	697	495	80	557	752	74	855	328	39	
2021	448	806	627	88	644	951	81	979	393	41	
2022	300	623	477	79	597	733	65	865	306	31	
2023	461	629	537	99	632	875	75	893	405	37	
2024*	540	722	628	101	727	1024	77	1027	467	39	

Appendix A. Details for S&P strategies

See [Tables A.1–A.9](#).

Appendix B. Details for NDX-100 LSTM strategies

See [Tables B.1–B.5](#).

Appendix C. Details for different hyperparameters

See [Figs. C.1–C.3](#) and [Tables C.1–C.6](#).

Appendix D. Details for LSTM

We used a standard approach to build our LSTM network. The model is compiled with the Adam optimizer, the loss function is categorical cross-entropy and the performance metric is accuracy.

D.1. Model training

The model is trained on the training data for $E = 10$ epochs and sliding window $W = 10$. The batch size is 32. The input data, X_{train} , is padded to ensure consistent sequence length. The target data, y_{train} , is one-hot encoded.

D.2. Application to S&P-500 and Nasdaq-100 price direction prediction

The LSTM model is applied to identify patterns in S&P-500 and Nasdaq-100 price direction sequences. It predicts the relationship between these financial instruments over time. The model is constructed in three steps:

1. Create LSTM (after importing standard modules and `tensorflow.keras`):

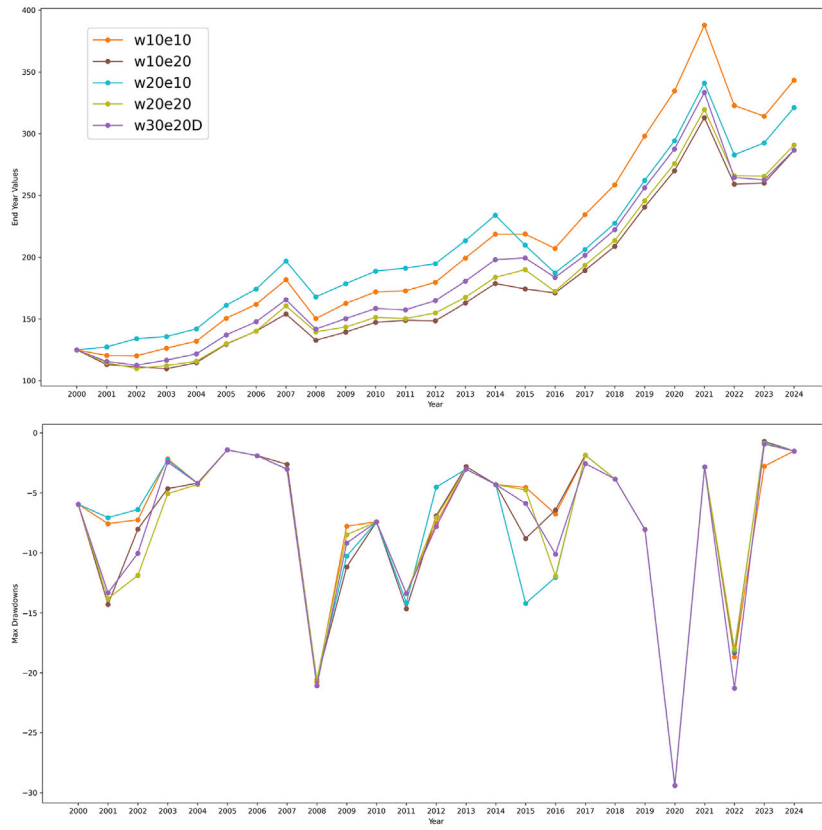


Fig. C.1. S&P-CO different hyperparameters.

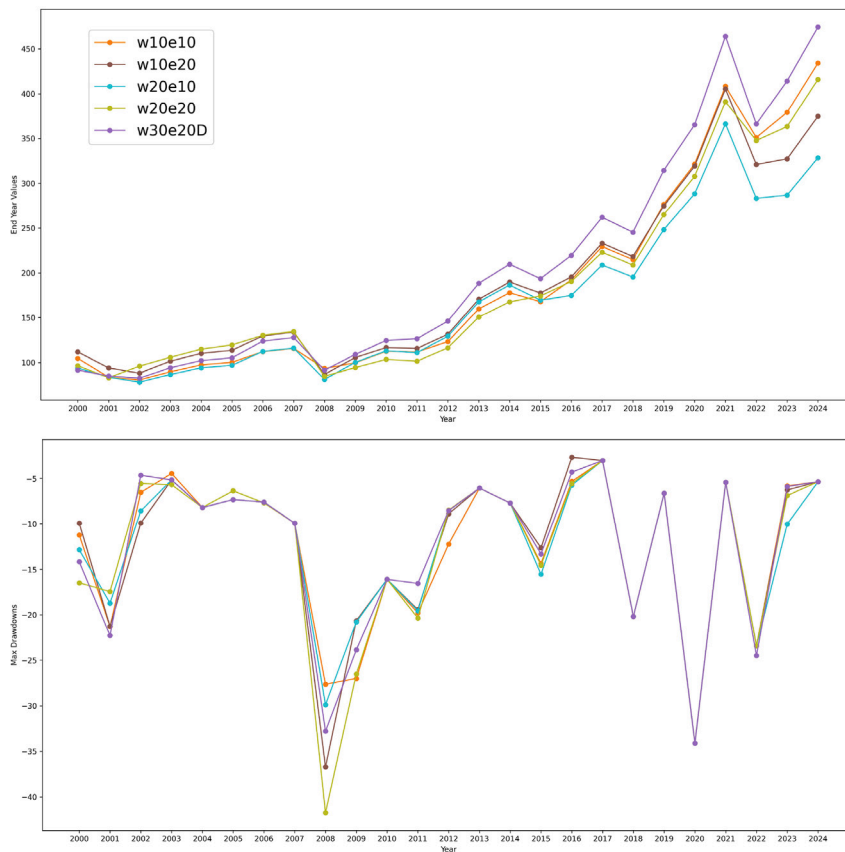


Fig. C.2. S&P-CC different hyperparameters.

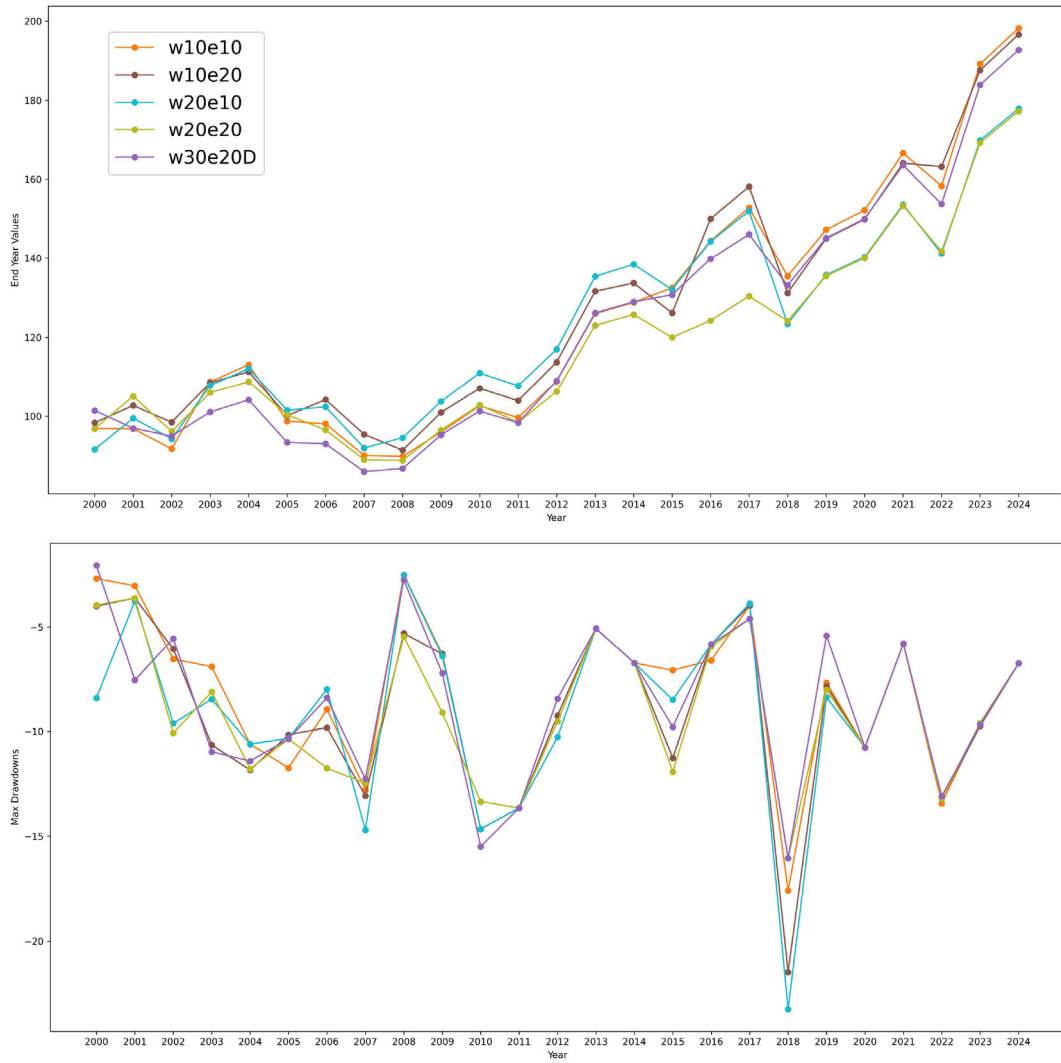


Fig. C.3. S&P-OC different hyperparameters.

Table B.2
Annual return for NDX-100 LSTM strategies.

Year	B&H		Training period							
	NDX	B	1Y			6M			3M	
			CO	CC	OC	CO	CC	OC	CC	OC
2000	-81.3	32.8	42.3	-34.7	-43.7	42.7	-6.8	-30.5	-32.0	-51.3
2001	-27.7	10.0	-3.0	3.8	0.1	-21.3	-2.6	5.7	6.4	5.1
2002	-39.4	2.3	-6.7	-11.5	-13.7	-10.0	-30.7	-23.6	-18.2	-12.1
2003	43.8	24.2	9.3	14.6	3.3	19.6	39.2	3.2	23.7	-0.2
2004	9.8	15.4	14.0	8.2	-4.3	8.2	13.3	6.2	12.6	-8.5
2005	2.3	11.3	16.5	4.0	-6.5	14.8	0.3	-10.6	-2.4	-13.7
2006	4.5	5.6	6.7	-1.6	-8.2	6.3	-3.1	-6.6	5.2	-1.8
2007	18.6	18.8	18.9	18.6	0.6	19.2	18.6	5.9	11.2	-4.2
2008	-41.0	-14.1	-15.1	-15.9	1.1	-13.9	-16.0	-12.3	-25.8	-19.3
2009	47.7	21.1	13.8	19.2	21.5	20.9	37.0	16.6	39.3	15.6
2010	17.4	7.8	16.6	17.4	2.1	11.9	12.0	-8.7	13.2	-1.6
2011	0.9	-10.4	-6.8	0.7	-0.4	-8.9	-5.4	-8.6	-18.1	-4.0
2012	14.7	0.9	8.0	19.4	4.2	4.1	26.6	3.9	7.6	1.0
2013	31.0	15.1	15.1	17.4	11.0	15.1	30.7	11.1	27.1	5.9
2014	18.4	17.0	16.9	18.4	-5.8	15.9	18.4	2.5	15.6	-6.4
2015	8.7	8.5	4.4	5.9	0.3	2.7	-9.5	0.8	-1.6	1.0
2016	8.2	8.5	-0.7	0.9	10.7	0.5	8.7	10.0	-10.4	-0.2
2017	30.6	14.3	19.3	30.6	9.9	20.0	29.0	9.2	27.7	6.2
2018	-2.7	11.3	11.4	-2.7	-10.0	12.1	-4.0	-11.7	0.3	-1.8
2019	37.4	14.5	19.8	37.4	8.6	21.0	33.2	6.4	25.8	6.9
2020	45.1	26.4	26.4	45.1	16.9	26.4	45.1	17.5	42.6	16.9
2021	28.8	14.9	16.0	28.8	11.7	16.0	28.4	11.7	21.4	8.9
2022	-33.9	-11.9	-23.0	-24.8	-11.0	-7.4	-23.8	-20.3	-23.0	-26.0
2023	55.7	3.2	1.0	12.6	25.8	5.8	19.6	18.0	32.8	20.7
2024*	42.8	35.0	32.8	42.8	7.2	35.0	42.8	6.8	38.4	10.2
max	55.7	35.0	42.3	45.1	25.8	42.7	45.1	18.0	42.6	20.7
min	-81.3	-14.1	-23.0	-34.7	-43.7	-21.3	-30.7	-30.5	-32.0	-51.3
M	14.7	11.3	13.8	12.6	1.1	12.1	13.3	3.9	11.2	-0.2
μ	9.6	11.3	10.2	10.2	1.3	10.3	12.0	0.1	8.8	-2.1
σ	33.0	12.3	14.5	19.6	13.7	15.0	21.4	13.0	21.4	14.9

B: 3-Month NDX CO (Night).

Table B.3
Annual maximum drawdown for NDX-100 LSTM strategies.

Year	B&H		Training period							
	NDX	B	1Y			6M			3M	
			CO	CC	OC	CO	CC	OC	CC	OC
2000	-37.2	-14.9	-14.9	-48.5	-43.6	-14.9	-36.5	-34.1	-45.2	-51.4
2001	-58.4	-8.0	-12.9	-1.8	-1.1	-22.7	-7.9	-8.3	-11.4	-9.5
2002	-51.9	-9.9	-11.3	-20.9	-14.3	-16.0	-33.2	-25.7	-21.4	-17.0
2003	-12.2	-6.9	-4.3	-6.8	-8.7	-4.6	-12.1	-14.7	-18.5	-20.5
2004	-15.9	-2.6	-4.5	-13.5	-21.4	-4.8	-9.6	-12.6	-14.6	-21.1
2005	-12.2	-3.0	-2.6	-10.7	-13.8	-2.6	-12.6	-15.4	-8.8	-13.6
2006	-17.4	-3.3	-3.2	-17.4	-10.0	-3.2	-12.1	-10.5	-9.9	-9.0
2007	-11.4	-4.9	-4.9	-11.4	-11.6	-4.9	-11.4	-9.8	-11.4	-13.7
2008	-49.5	-14.7	-16.8	-18.5	-13.4	-16.0	-18.9	-12.6	-26.1	-20.0
2009	-18.3	-4.3	-10.0	-5.4	-8.7	-3.0	-6.5	-7.6	-12.9	-13.7
2010	-15.9	-7.5	-7.5	-15.9	-15.5	-7.5	-15.9	-15.1	-13.3	-11.2
2011	-16.1	-11.5	-13.9	-16.1	-13.7	-14.8	-19.9	-17.5	-28.2	-15.0
2012	-11.9	-7.6	-5.5	-11.5	-13.4	-5.9	-10.4	-10.8	-7.6	-8.5
2013	-6.2	-3.2	-3.2	-5.1	-4.4	-3.2	-6.2	-4.4	-6.2	-4.4
2014	-8.5	-5.2	-5.2	-8.5	-15.6	-5.2	-8.5	-7.7	-7.2	-13.4
2015	-13.9	-4.5	-11.9	-13.9	-10.1	-7.5	-19.8	-5.2	-10.0	-7.1
2016	-12.0	-5.0	-10.7	-12.0	-8.4	-6.4	-9.7	-9.4	-15.1	-7.9
2017	-5.1	-1.6	-2.4	-5.1	-6.3	-2.4	-5.1	-6.3	-5.1	-6.3
2018	-23.2	-5.6	-4.5	-23.2	-20.0	-4.6	-24.2	-16.8	-15.7	-10.3
2019	-11.0	-11.3	-11.3	-11.0	-5.0	-11.3	-11.0	-8.7	-11.0	-7.0
2020	-28.6	-27.4	-27.4	-28.6	-13.9	-27.4	-28.6	-14.1	-28.6	-10.9
2021	-10.9	-6.2	-6.2	-10.9	-9.7	-6.2	-10.9	-9.7	-10.9	-9.7
2022	-35.2	-12.4	-23.2	-32.4	-19.3	-10.1	-23.6	-21.3	-24.4	-25.8
2023	-10.9	-4.7	-0.9	-7.4	-10.6	-4.7	-10.9	-10.6	-8.0	-9.6
2024*	-7.1	-2.1	-2.1	-7.1	-9.8	-2.1	-7.1	-9.8	-7.1	-2.7
max	-58.4	-27.4	-27.4	-48.5	-43.6	-27.4	-36.5	-34.1	-45.2	-51.4
min	-5.1	-1.6	-0.9	-1.8	-1.1	-2.1	-5.1	-4.4	-5.1	-2.7
M	-13.9	-5.6	-6.2	-11.5	-11.6	-5.9	-11.4	-10.6	-11.4	-10.9
μ	-20.0	-7.5	-8.9	-14.6	-12.9	-8.5	-14.9	-12.7	-15.1	-13.6
σ	14.9	5.6	6.7	10.2	8.0	6.7	8.6	6.6	9.3	9.6

Table B.4
Annual volatility for NDX-100 LSTM strategies.

Year	B&H		Training period							
	NDX	B	1Y			6M			3M	
			CO	CC	OC	CO	CC	OC	CC	OC
2000	65.2	21.8	24.8	53.6	39.3	24.5	44.9	36.6	40.5	36.3
2001	54.2	15.3	17.5	5.9	2.0	15.8	10.7	11.0	21.2	17.8
2002	41.7	9.5	6.3	15.2	7.9	12.0	18.8	16.9	21.0	13.4
2003	24.4	10.7	6.3	17.4	15.7	8.6	23.0	19.7	21.9	20.1
2004	17.3	6.8	7.8	16.5	15.6	7.1	12.5	11.1	12.4	12.5
2005	13.2	5.2	5.5	13.1	8.5	5.4	13.0	8.5	10.0	6.9
2006	15.5	6.1	6.5	15.0	9.4	6.5	11.7	8.1	11.9	9.3
2007	18.2	8.9	8.9	18.2	14.1	8.9	18.2	13.2	18.0	9.8
2008	40.0	11.5	20.3	22.0	17.6	18.8	14.8	14.3	13.2	15.7
2009	25.3	10.6	11.4	9.9	12.0	8.5	15.3	13.8	20.8	16.4
2010	19.3	11.1	11.4	19.3	15.2	11.2	18.8	13.9	16.5	12.1
2011	23.7	8.6	12.7	23.7	17.5	10.2	20.5	16.0	20.9	16.1
2012	15.3	8.0	8.6	14.5	12.7	8.6	12.2	12.2	9.7	10.9
2013	11.9	7.1	7.1	9.4	9.7	7.1	9.8	8.6	11.1	8.1
2014	13.8	7.4	7.4	13.8	11.6	7.4	13.8	9.4	13.4	10.0
2015	18.0	9.0	13.4	17.9	14.4	8.3	14.9	9.7	12.0	10.8
2016	16.1	8.4	9.9	14.3	11.8	8.6	12.6	12.4	10.4	10.2
2017	10.3	5.2	5.5	10.3	8.5	5.5	10.3	8.5	10.3	8.3
2018	22.9	10.4	12.0	22.9	19.9	12.0	22.9	18.7	19.0	15.3
2019	16.2	9.3	9.9	16.2	10.0	9.9	16.1	9.8	14.4	9.4
2020	35.7	24.6	24.6	35.7	22.6	24.6	35.7	22.5	35.6	21.9
2021	18.2	9.8	10.3	18.2	14.6	10.3	18.2	14.6	17.0	14.3
2022	32.2	8.7	14.2	26.6	24.8	10.2	16.3	20.1	13.3	15.6
2023	17.9	5.9	1.7	9.2	13.5	4.9	13.2	12.8	13.5	13.4
2024*	15.1	9.5	9.5	15.1	11.9	9.5	15.1	11.2	15.0	7.2
max	65.2	24.6	24.8	53.6	39.3	24.6	44.9	36.6	40.5	36.3
min	10.3	5.2	1.7	5.9	2.0	4.9	9.8	8.1	9.7	6.9
M	18.2	9.0	9.9	16.2	13.5	8.9	15.1	12.8	14.4	12.5
μ	24.1	10.0	10.9	18.2	14.4	10.6	17.3	14.1	16.9	13.7
σ	13.7	4.6	5.7	9.7	7.1	5.2	7.9	6.1	7.5	6.2

Table B.5
Annual Sharp Ratio for NDX-100 LSTM Strategies.

Year	B&H		Training Period							
	NDX	B	1Y			6M			3M	
			CO	CC	OC	CO	CC	OC	CC	OC
2000	-1.2	1.5	1.7	-0.6	-1.1	1.7	-0.2	-0.8	-0.8	-1.4
2001	-0.5	0.7	-0.2	0.6	0.0	-1.4	-0.2	0.5	0.3	0.3
2002	-0.9	0.2	-1.1	-0.8	-1.7	-0.8	-1.6	-1.4	-0.9	-0.9
2003	1.8	2.3	1.5	0.8	0.2	2.3	1.7	0.2	1.1	0.0
2004	0.6	2.2	1.8	0.5	-0.3	1.1	1.1	0.6	1.0	-0.7
2005	0.2	2.2	3.0	0.3	-0.8	2.7	0.0	-1.2	-0.2	-2.0
2006	0.3	0.9	1.0	-0.1	-0.9	1.0	-0.3	-0.8	0.4	-0.2
2007	1.0	2.1	2.1	1.0	0.0	2.1	1.0	0.4	0.6	-0.4
2008	-1.0	-1.2	-0.7	-0.7	0.1	-0.7	-1.1	-0.9	-2.0	-1.2
2009	1.9	2.0	1.2	1.9	1.8	2.5	2.4	1.2	1.9	1.0
2010	0.9	0.7	1.5	0.9	0.1	1.1	0.6	-0.6	0.8	-0.1
2011	0.0	-1.2	-0.5	0.0	0.0	-0.9	-0.3	-0.5	-0.9	-0.2
2012	1.0	0.1	0.9	1.3	0.3	0.5	2.2	0.3	0.8	0.1
2013	2.6	2.1	2.1	1.8	1.1	2.1	3.1	1.3	2.4	0.7
2014	1.3	2.3	2.3	1.3	-0.5	2.1	1.3	0.3	1.2	-0.6
2015	0.5	0.9	0.3	0.3	0.0	0.3	-0.6	0.1	-0.1	0.1
2016	0.5	1.0	-0.1	0.1	0.9	0.1	0.7	0.8	-1.0	0.0
2017	3.0	2.8	3.5	3.0	1.2	3.6	2.8	1.1	2.7	0.7
2018	-0.1	1.1	0.9	-0.1	-0.5	1.0	-0.2	-0.6	0.0	-0.1
2019	2.3	1.6	2.0	2.3	0.9	2.1	2.1	0.7	1.8	0.7
2020	1.3	1.1	1.1	1.3	0.7	1.1	1.3	0.8	1.2	0.8
2021	1.6	1.5	1.6	1.6	0.8	1.6	1.6	0.8	1.3	0.6
2022	-1.1	-1.4	-1.6	-0.9	-0.4	-0.7	-1.5	-1.0	-1.7	-1.7
2023	3.1	0.5	0.6	1.4	1.9	1.2	1.5	1.4	2.4	1.5
2024*	2.8	3.7	3.5	2.8	0.6	3.7	2.8	0.6	2.6	1.4
max	3.1	3.7	3.5	3.0	1.9	3.7	3.1	1.4	2.7	1.5
min	-1.2	-1.4	-1.6	-0.9	-1.7	-1.4	-1.6	-1.4	-2.0	-2.0
M	0.9	1.1	1.2	0.8	0.1	1.1	1.0	0.3	0.8	0.0
μ	0.9	1.2	1.1	0.8	0.2	1.2	0.8	0.1	0.6	-0.1
σ	1.3	1.2	1.3	1.1	0.9	1.4	1.4	0.8	1.3	0.9

Table C.1
SPY-CO end balance and Max drawdown for different hyperparameters.

Year	w10e10		w10e20		w20e10		w20e20		w30e20D	
	val	mdd	val	mdd	val	mdd	val	mdd	val	mdd
2000	124	-6.0	124	-6.0	124	-6.0	124	-6.0	124	-6.0
2001	120	-7.6	113	-14.3	127	-7.1	114	-13.8	115	-13.3
2002	120	-7.3	111	-8.0	134	-6.4	109	-11.9	112	-10.0
2003	126	-2.2	109	-4.6	135	-2.3	112	-5.1	116	-2.4
2004	131	-4.2	114	-4.2	141	-4.2	115	-4.3	121	-4.2
2005	150	-1.4	129	-1.4	161	-1.4	129	-1.4	137	-1.4
2006	161	-1.9	140	-1.9	174	-1.9	140	-1.9	147	-1.9
2007	181	-3.0	153	-2.6	196	-3.0	160	-3.0	165	-3.0
2008	150	-20.8	132	-20.6	167	-20.6	139	-20.6	141	-21.1
2009	162	-7.8	139	-11.2	178	-10.3	143	-8.5	150	-9.2
2010	171	-7.4	147	-7.4	188	-7.4	151	-7.4	158	-7.4
2011	172	-13.4	148	-14.7	191	-14.2	150	-13.4	157	-13.4
2012	179	-7.5	148	-6.9	194	-4.5	154	-7.1	164	-7.8
2013	199	-3.0	162	-2.8	213	-3.0	167	-3.0	180	-3.0
2014	218	-4.3	178	-4.3	234	-4.3	183	-4.3	197	-4.3
2015	218	-4.6	174	-8.8	209	-14.2	189	-4.8	199	-5.9
2016	207	-6.8	171	-6.4	187	-12.0	172	-11.9	183	-10.1
2017	234	-1.9	189	-1.9	206	-1.9	193	-1.9	201	-2.6
2018	258	-3.9	208	-3.9	227	-3.9	213	-3.9	222	-3.9
2019	298	-8.1	240	-8.1	262	-8.1	245	-8.1	256	-8.1
2020	334	-29.4	270	-29.4	294	-29.4	275	-29.4	287	-29.4
2021	387	-2.8	312	-2.8	340	-2.8	319	-2.8	333	-2.8
2022	322	-18.7	259	-18.3	282	-18.1	265	-18.0	264	-21.3
2023	314	-2.8	260	-0.7	292	-0.9	265	-0.9	262	-0.9
2024	343	-1.5	286	-1.5	321	-1.5	290	-1.5	286	-1.5
max	N/A	-29.4	N/A	-29.4	N/A	-29.4	N/A	-29.4	N/A	-29.4
min	N/A	-1.4	N/A	-0.7	N/A	-0.9	N/A	-0.9	N/A	-0.9
M	N/A	-4.6	N/A	-6.0	N/A	-4.5	N/A	-5.1	N/A	-5.9
μ	N/A	-7.1	N/A	-7.7	N/A	-7.6	N/A	-7.8	N/A	-7.8
σ	N/A	6.8	N/A	7.0	N/A	7.1	N/A	7.0	N/A	7.2

Table C.2
SPY-CC different hyperparameters.

Year	w10e10		w10e20		w20e10		w20e20		w30e20D	
	val	mdd	val	mdd	val	mdd	val	mdd	val	mdd
2000	104	-11.2	111	-9.9	93	-12.8	96	-16.5	91	-14.2
2001	83	-21.3	93	-21.3	83	-18.7	82	-17.4	84	-22.3
2002	80	-6.5	88	-9.9	78	-8.6	95	-5.6	82	-4.6
2003	89	-4.4	101	-5.2	86	-5.2	105	-5.7	94	-5.2
2004	97	-8.2	110	-8.2	93	-8.2	114	-8.2	102	-8.2
2005	100	-7.3	113	-7.3	96	-7.3	119	-6.3	105	-7.3
2006	112	-7.6	129	-7.6	112	-7.6	130	-7.7	123	-7.6
2007	115	-9.9	133	-9.9	116	-9.9	134	-9.9	127	-9.9
2008	93	-27.6	86	-36.7	81	-29.9	84	-41.7	91	-32.8
2009	99	-27.0	105	-20.6	100	-20.8	94	-26.5	109	-23.9
2010	112	-16.1	116	-16.1	112	-16.1	103	-16.1	124	-16.1
2011	111	-19.8	115	-19.4	111	-19.5	101	-20.3	126	-16.5
2012	123	-12.2	131	-8.9	129	-8.5	116	-8.5	146	-8.5
2013	159	-6.0	170	-6.0	167	-6.0	150	-6.0	188	-6.0
2014	177	-7.7	189	-7.7	186	-7.7	167	-7.7	209	-7.7
2015	167	-14.4	177	-12.6	169	-15.5	174	-14.5	193	-13.3
2016	192	-5.3	195	-2.7	174	-5.7	190	-5.5	219	-4.3
2017	229	-3.0	233	-3.0	208	-3.0	223	-3.0	261	-3.0
2018	214	-20.2	218	-20.2	195	-20.2	208	-20.2	245	-20.2
2019	276	-6.6	274	-6.6	248	-6.6	264	-6.6	314	-6.6
2020	321	-34.1	319	-34.1	288	-34.1	307	-34.1	365	-34.1
2021	408	-5.4	405	-5.4	366	-5.4	391	-5.4	464	-5.4
2022	351	-23.4	321	-23.4	283	-23.4	347	-23.4	366	-24.5
2023	379	-5.8	327	-6.3	286	-10.0	363	-6.9	414	-5.9
2024	434	-5.4	374	-5.4	328	-5.4	416	-5.4	474	-5.4
max	N/A	-34.1	N/A	-36.7	N/A	-34.1	N/A	-41.7	N/A	-34.1
min	N/A	-3.0	N/A	-2.7	N/A	-3.0	N/A	-3.0	N/A	-3.0
M	N/A	-8.2	N/A	-8.9	N/A	-8.6	N/A	-8.2	N/A	-8.2
μ	N/A	-12.7	N/A	-12.6	N/A	-12.7	N/A	-13.2	N/A	-12.5
σ	N/A	8.6	N/A	9.2	N/A	8.2	N/A	9.9	N/A	9.0

Table C.3
S&P-OC Different hyperparameters.

Year	N10E10		N10E20		N20E10		N20E20		N30E10		N30E20		N30E20D	
	val	mdd	val	mdd	val	mdd	val	mdd	val	mdd	val	mdd	val	mdd
2000	96	-2.7	98	-4.0	91	-8.4	96	-4.0	92	-7.1	94	-5.9	101	-2.1
2001	96	-3.0	102	-3.6	99	-3.8	105	-3.6	96	-3.6	99	-3.6	96	-7.6
2002	91	-6.5	98	-6.1	94	-9.6	96	-10.1	87	-12.3	84	-18.8	94	-5.6
2003	108	-6.9	108	-10.6	107	-8.5	105	-8.1	105	-9.7	92	-7.1	101	-11.0
2004	113	-10.6	111	-11.8	112	-10.6	108	-11.8	109	-10.7	94	-11.4	104	-11.4
2005	98	-11.7	100	-10.2	101	-10.3	100	-10.4	99	-11.8	86	-10.2	93	-10.4
2006	98	-8.9	104	-9.8	102	-8.0	96	-11.7	101	-5.8	90	-4.3	93	-8.4
2007	90	-12.8	95	-13.1	91	-14.7	89	-12.5	94	-11.7	84	-12.0	85	-12.3
2008	89	-2.5	91	-5.3	94	-2.5	88	-5.5	88	-7.0	82	-7.7	86	-2.8
2009	95	-6.3	100	-6.3	103	-6.4	96	-9.1	92	-7.6	96	-5.2	95	-7.2
2010	102	-14.7	107	-14.7	110	-14.7	102	-13.4	98	-14.7	98	-12.8	101	-15.5
2011	99	-13.7	103	-13.7	107	-13.7	98	-13.7	95	-13.7	96	-13.7	98	-13.7
2012	108	-9.5	113	-9.2	116	-10.3	106	-9.5	106	-8.3	106	-8.1	108	-8.4
2013	125	-5.1	131	-5.1	135	-5.1	123	-5.1	122	-5.1	122	-5.1	126	-5.1
2014	128	-6.7	133	-6.7	138	-6.7	125	-6.7	125	-6.7	125	-6.7	128	-6.7
2015	132	-7.1	126	-11.3	132	-8.5	119	-11.9	133	-7.1	116	-14.0	130	-9.8
2016	144	-6.6	150	-5.8	144	-5.8	124	-6.0	144	-5.8	132	-5.9	139	-5.8
2017	152	-4.0	158	-4.0	151	-3.9	130	-4.6	152	-4.1	142	-3.1	146	-4.6
2018	135	-1.6	131	-21.5	123	-23.2	124	-16.1	146	-16.1	136	-14.7	133	-16.1
2019	147	-7.7	145	-7.8	135	-8.4	135	-8.0	170	-4.8	159	-2.9	145	-5.4
2020	152	-10.8	149	-10.8	140	-10.8	140	-10.8	176	-10.8	163	-10.8	150	-10.8
2021	166	-5.8	164	-5.8	153	-5.8	153	-5.8	193	-5.8	178	-5.8	163	-5.8
2022	158	-13.4	163	-13.2	141	-13.2	141	-13.2	186	-13.2	165	-13.2	153	-13.1
2023	189	-9.6	187	-9.7	169	-9.6	169	-9.6	221	-9.7	192	-9.9	183	-9.7
2024	198	-6.7	196	-6.7	177	-6.7	177	-6.7	232	-6.7	201	-6.7	192	-6.7
max	N/A	-17.6	N/A	-21.5	N/A	-23.2	N/A	-16.1	N/A	-16.1	N/A	-18.8	N/A	-16.1
min	N/A	-2.5	N/A	-3.6	N/A	-2.5	N/A	-3.6	N/A	-3.6	N/A	-2.9	N/A	-2.1
M	N/A	-7.1	N/A	-9.2	N/A	-8.5	N/A	-9.5	N/A	-7.6	N/A	-7.7	N/A	-8.4
μ	N/A	-8.4	N/A	-9.1	N/A	-9.2	N/A	-9.1	N/A	-8.8	N/A	-8.8	N/A	-8.6
σ	N/A	4.0	N/A	4.2	N/A	4.4	N/A	3.4	N/A	3.5	N/A	4.2	N/A	3.7

Table C.4
Nasdaq-OC end balance and Max drawdown for different hyperparameters.

Year	w10e10		w10e20		w20e10		w20e20		w30e20D	
	val	mdd	val	mdd	val	mdd	val	mdd	val	mdd
2000	48	-51.4	53	-48.1	48	-53.8	54	-48.3	55	-46.4
2001	51	-9.5	58	-9.5	51	-9.5	53	-15.5	57	-11.9
2002	45	-17.0	41	-32.2	48	-17.7	39	-30.2	44	-25.7
2003	45	-20.5	42	-19.7	50	-20.1	40	-16.9	44	-20.1
2004	41	-21.1	35	-27.6	46	-21.6	35	-25.3	41	-19.9
2005	35	-13.6	28	-17.2	42	-8.2	30	-15.4	34	-15.4
2006	34	-9.0	27	-8.7	43	-5.9	29	-7.9	35	-6.0
2007	33	-13.7	27	-10.8	40	-14.1	26	-16.4	34	-13.4
2008	26	-20.0	26	-12.0	36	-11.6	22	-22.2	31	-16.2
2009	30	-13.7	29	-15.9	39	-15.3	24	-14.4	35	-16.6
2010	30	-11.2	29	-11.9	41	-11.2	24	-11.2	36	-11.4
2011	29	-15.0	29	-14.6	38	-16.0	24	-17.0	37	-15.8
2012	29	-8.5	29	-9.4	39	-10.2	23	-12.6	38	-8.5
2013	31	-4.4	29	-6.8	38	-6.9	23	-5.9	39	-6.1
2014	29	-13.4	29	-9.0	35	-14.3	23	-7.3	37	-12.7
2015	29	-7.1	28	-6.6	34	-7.7	23	-7.7	36	-7.5
2016	29	-7.9	29	-6.7	36	-5.2	23	-8.3	38	-6.5
2017	30	-6.3	31	-6.3	37	-6.3	25	-6.3	39	-6.3
2018	30	-10.3	31	-10.8	36	-11.8	24	-10.8	37	-13.1
2019	32	-7.0	32	-5.4						

Table C.5
Nasdaq-CC End Balance and Max Drawdown for Different Hyperparameters.

Year	w10e10		w10e20		w20e10		w20e20		w30e20D	
	val	mdd	val	mdd	val	mdd	val	mdd	val	mdd
2000	70	-45.2	72	-44.2	68	-47.0	70	-45.2	86	-41.5
2001	74	-11.4	63	-21.2	58	-24.2	75	-11.4	72	-18.3
2002	63	-21.4	58	-19.7	49	-20.8	66	-19.5	62	-20.7
2003	81	-18.5	75	-19.4	68	-12.5	88	-16.4	81	-18.4
2004	91	-14.6	84	-12.9	74	-14.4	101	-10.8	92	-12.6
2005	88	-8.8	89	-7.5	72	-8.7	100	-7.5	94	-7.6
2006	94	-9.9	96	-9.5	77	-10.4	108	-8.8	101	-10.1
2007	105	-11.4	107	-11.4	87	-11.4	121	-11.4	115	-11.4
2008	77	-26.1	82	-21.6	68	-20.9	107	-19.5	95	-16.0
2009	107	-12.9	110	-18.0	98	-15.1	141	-15.9	131	-15.5
2010	123	-13.3	116	-14.7	120	-13.3	176	-13.3	160	-13.3
2011	102	-28.2	110	-17.6	115	-17.5	166	-22.8	150	-18.2
2012	110	-7.6	116	-8.0	119	-11.3	176	-9.5	156	-10.0
2013	140	-6.2	148	-6.2	147	-6.2	207	-6.2	197	-6.2
2014	160	-7.2	170	-7.9	157	-9.6	230	-7.8	219	-7.3
2015	157	-10.0	156	-16.0	164	-6.0	224	-11.0	226	-6.0
2016	138	-15.1	154	-9.1	167	-5.2	200	-13.5	206	-12.3
2017	176	-5.1	198	-5.1	209	-5.1	249	-5.1	258	-5.1
2018	180	-15.7	175	-28.0	188	-22.6	254	-17.0	250	-18.3
2019	226	-11.0	227	-11.0	247	-11.0	313	-11.0	322	-11.0
2020	328	-28.6	331	-28.6	341	-28.6	451	-28.6	458	-28.6
2021	392	-10.9	408	-10.9	429	-10.9	549	-10.9	582	-10.9
2022	306	-24.4	328	-20.5	344	-26.5	400	-29.8	407	-30.8
2023	404	-8.0	425	-9.3	473	-9.8	498	-11.6	542	-7.8
2024	466	-7.1	501	-7.1	526	-7.4	577	-7.1	616	-7.1
max	N/A	-45.2	N/A	-44.2	N/A	-47.0	N/A	-45.2	N/A	-41.5
min	N/A	-5.1	N/A	-5.1	N/A	-5.1	N/A	-5.1	N/A	-5.1
M	N/A	-11.4	N/A	-12.9	N/A	-11.4	N/A	-11.4	N/A	-12.3
μ	N/A	-15.1	N/A	-15.4	N/A	-15.0	N/A	-14.9	N/A	-14.6
σ	N/A	9.3	N/A	8.9	N/A	9.5	N/A	9.0	N/A	8.7

Table C.6
Nasdaq-CO end balance and Max drawdown for different hyperparameters.

Year	w10e10		w10e20		w20e10		w20e20		w30e20D	
	val	mdd	val	mdd	val	mdd	val	mdd	val	mdd
2000	128	-14.9	129	-14.9	117	-14.9	118	-14.9	139	-14.9
2001	141	-8.0	131	-8.0	113	-8.0	134	-8.0	150	-8.0
2002	144	-9.9	128	-9.9	120	-9.9	141	-9.9	147	-9.9
2003	179	-6.9	159	-7.4	146	-7.3	170	-7.5	179	-8.9
2004	208	-2.6	186	-2.6	166	-3.1	186	-4.6	205	-2.7
2005	232	-3.0	213	-3.4	191	-3.0	214	-2.7	233	-2.6
2006	246	-3.3	227	-3.7	199	-4.0	224	-3.5	244	-4.1
2007	292	-4.9	274	-4.9	234	-4.9	275	-4.9	291	-4.9
2008	251	-14.7	221	-20.6	208	-14.3	217	-20.8	252	-13.6
2009	303	-4.3	256	-4.7	254	-3.5	249	-6.2	284	-7.6
2010	327	-7.5	283	-7.5	268	-8.1	271	-7.4	311	-7.5
2011	294	-11.5	250	-13.2	247	-10.3	249	-12.9	276	-12.9
2012	297	-7.6	253	-8.7	249	-7.6	257	-6.2	283	-5.4
2013	342	-3.2	291	-3.2	286	-3.2	295	-3.2	325	-3.2
2014	400	-5.2	340	-5.2	331	-5.2	345	-5.2	380	-5.2
2015	431	-4.5	363	-4.5	383	-3.6	378	-6.2	414	-5.9
2016	470	-5.0	393	-5.0	415	-5.0	395	-5.9	448	-5.0
2017	538	-1.6	441	-1.8	485	-1.6	455	-1.7	522	-1.6
2018	599	-5.6	471	-6.8	534	-6.3	500	-5.8	588	-5.4
2019	685	-11.3	521	-11.3	605	-11.3	567	-11.3	677	-11.3
2020	855	-27.4	650	-27.4	755	-27.4	707	-27.4	841	-27.4
2021	979	-6.2	758	-6.2	868	-6.2	823	-6.2	993	-6.2
2022	865	-12.4	678	-12.2	721	-17.0	723	-13.5	863	-13.9
2023	892	-4.7	708	-4.5	729	-5.4	751	-5.0	902	-5.1
2024	1027	-2.1	814	-2.1	838	-2.1	864	-2.1	1038	-2.1
max	N/A	-27.4	N/A	-27.4	N/A	-27.4	N/A	-27.4	N/A	-27.4
min	N/A	-1.6	N/A	-1.8	N/A	-1.6	N/A	-1.7	N/A	-1.6
M	N/A	-5.6	N/A	-6.2	N/A	-6.2	N/A	-6.2	N/A	-5.9
μ	N/A	-7.5	N/A	-8.0	N/A	-7.7	N/A	-8.1	N/A	-7.8
σ	N/A	5.6	N/A	6.0	N/A	5.8	N/A	6.0	N/A	5.6

```

1 model = Sequential()
2 model.add(LSTM(50, input_shape=(W
   =10, 1))) # 50 refers to the
   number of units in the LSTM
   layer.
3 model.add(Dense(2, activation='
   softmax')) # 2 output

```

2. compile LSTM:

```

1 model.compile(optimizer='adam', loss
   ='categorical_crossentropy',
2               metrics=['accuracy'])

```

3. train LSTM:

```

1 model.fit(X_train, y_train, epochs
   =10, batch_size=32)

```

Appendix E. Results and analysis of S& P-500 predictions using LSTM

The results for S&P-500 is shown in Fig. 5 and the results for S&P-500 trading are shown in Table E.1 (a detailed summary of annual balances is presented in Appendix A). From Table 3, it is clear that using LSTM for one year yields better results for CO, CC, and OC strategies compared to six-month and three-month periods. Table E.1 shows that CO, OC, and CC LSTM predictions are not significantly different from the buy-and-hold strategy. However, combining CO and OC may improve results, leading to Strategy A (see Fig. E.1):

The summary results for annual return, maximum drawdown, volatility, and Sharpe ratio are presented in Table E.1 with detailed annual results of these metrics can be found in Appendix A. Fig. 5 shows that our combined CO and OC LSTM predictions (strategy A), achieve a return of \$680, significantly outperforming the buy-and-hold S&P return of \$379 (about 80%). Additionally, from Table E.1, it is evident that Strategy A outperforms the CC strategy, providing higher annual returns ($M = 12.2\%$ vs. 8.7%), lower maximum drawdowns ($M = -8.0\%$ vs. -8.2%), and lower volatility ($M = 11.6\%$ vs. 12.6%). From Table E.1, Strategy A also shows a lower standard deviation of annual returns ($\sigma = 14.1\%$) compared to the buy-and-hold strategy ($\sigma = 19.2\%$). Table E.1 also shows that Strategy A using LSTM with one-year training data achieves the highest end balance, highlighting the advantage of longer training durations.

Next, let us examine the number of transactions proportional to the cost of implementing any strategy. For S&P, investing only in overnight (CO-strategy), daytime (OC strategy) and 24-h (CC) strategy requires (on average) 19, 21, and 18 transactions, respectively. Combining CO and OC in strategy A increases this number almost 7-fold to 144.

Appendix F. Results and analysis of nasdaq-100 predictions using LSTM

The summary results for annual return, maximum drawdown, volatility, and Sharpe ratio are presented in Table F.1. (detailed results of these metrics can be found in Appendix B). Table E.1 shows that the 3-month “Overnight” CO LSTM prediction for Nasdaq-100 is the best, indicating that Nasdaq-100 benefits from shorter training durations.

Fig. 6 illustrates the 3-month “Overnight” CO strategy yielding the highest end balance of \$1027, surpassing the 3-month “24-h” CC result of \$467 and the “Daytime” OC result of \$39. The final result outperforms the buy-and-hold Nasdaq-100 return of \$540. Additionally,

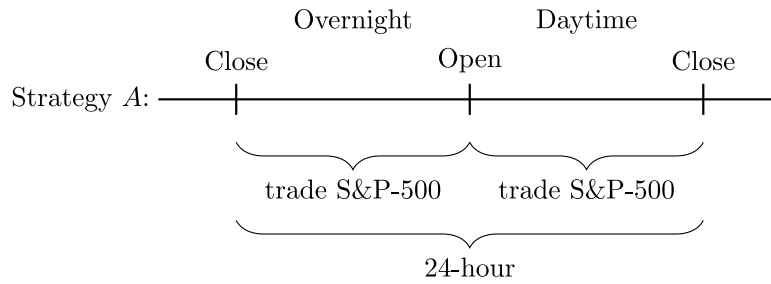


Fig. E.1. Strategy A: Trading cycle for S&P-500 over 24 h.

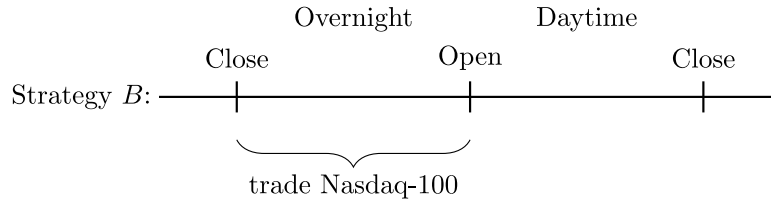


Fig. F.1. Strategy B: Trading cycle for Nasdaq-100 over a day.

Table E.1 Performance comparison of S&P-500 LSTM strategies.

Year	B&H		Training period									
	S&P	A	1Y			6M			3M			
			CO	CC	OC	CO	CC	OC	CO	CC	OC	
Annual return												
max	33.5	33.0	26.7	33.5	20.9	25.8	33.5	18.6	22.7	28.9	16.2	
min	-37.7	-21.5	-17.3	-20.5	-11.8	-15.7	-41.6	-19.1	-22.5	-37.9	-19.4	
M	11.2	12.2	7.4	8.7	3.4	7.3	7.0	1.6	5.8	4.3	1.1	
μ	6.4	9.9	6.2	7.3	3.5	6.0	5.2	1.9	4.7	3.2	0.3	
σ	19.2	14.1	10.5	14.2	8.4	9.4	16.6	8.8	10.6	15.1	9.8	
Maximum drawdown												
max	-47.9	-32.4	-29.4	-34.1	-17.6	-29.4	-43.1	-22.9	-29.4	-44.1	-23.9	
min	-3.0	-2.3	-1.4	-3.0	-2.5	-1.4	-3.0	-3.7	-1.4	-3.7	-3.8	
M	-10.3	-8.0	-4.6	-8.2	-7.1	-3.9	-9.0	-9.6	-5.2	-9.0	-8.0	
μ	-15.5	-10.7	-7.1	-12.7	-8.4	-6.5	-13.1	-9.5	-6.8	-12.4	-9.9	
σ	11.4	7.2	6.8	8.6	4.0	6.2	10.2	4.7	6.5	9.7	5.5	
Volatility												
max	41.3	29.4	24.7	33.6	20.1	24.7	33.6	19.4	24.2	30.3	19.4	
min	6.7	6.1	1.9	5.1	2.7	3.7	3.5	3.5	3.5	5.8	4.8	
M	15.6	11.6	7.5	12.6	9.5	6.9	12.2	9.6	6.5	10.5	8.4	
μ	17.7	13.5	8.5	14.3	10.1	8.1	13.8	10.1	7.8	12.7	9.7	
σ	8.3	5.5	5.4	6.7	4.2	4.9	7.0	3.6	4.7	6.0	3.6	
Sharp ratio												
max	3.1	3.2	3.7	3.1	1.9	3.3	3.1	2.1	3.3	2.6	1.6	
min	-1.2	-0.9	-1.7	-1.9	-1.3	-0.8	-1.3	-1.5	-1.9	-2.4	-1.8	
M	0.8	0.8	0.8	0.6	0.4	1.1	0.4	0.1	1.4	0.4	0.1	
μ	0.7	0.9	0.9	0.7	0.4	1.0	0.6	0.2	0.8	0.4	0.1	
σ	1.2	1.2	1.5	1.2	0.8	1.2	1.2	0.9	1.4	1.2	0.9	

Strategy A: Combine 1Y CO (“overnight”) and OC (“day”).

Table F.1 reveals that Nasdaq-100 has high return volatility, supporting the effectiveness of using a 3-month training period. The “Daytime” OC strategy generally does not yield significant profits. As the training duration decreases, the “Daytime” OC strategy’s performance diminishes further, from \$101 to \$39. Therefore, we decide to use the “Overnight” CO strategy as our Strategy B (see Fig. F.1):

Table F.1 shows that strategy B has an advantage in maximum drawdown (MDD). Strategy B achieves a median max drawdown of $M = -5.6\%$ (vs. $M = -13.9\%$ for buy-and-hold Nasdaq-100). Strategy B has a median volatility of $M = 9.0\%$ (vs. $M = 18.2\%$ for buy-and-hold Nasdaq-100). Furthermore, strategy B has a higher median Sharpe

ratio of $M = 1.1$ (vs. $M = 0.9$ for buy-and-hold Nasdaq). Additionally, the standard deviation of annual returns for Strategy B is $\sigma = 14.5\%$ and is lower than both buy-and-hold Nasdaq-100 ($\sigma = 33.0\%$) and CC ($\sigma = 19.6\%$).

Next, we examine the number of transactions to implement the “overnight” strategy B for Nasdaq. This strategy requires only 18 transactions per year, on average. This is much lower (18 vs. 144) than is required for strategy A for S&P-500. Comparing strategies A and B, we see that B is superior to A. It gives 90% more return than buy-and-hold (\$1027 vs. \$540) with 18 transactions per year on average. By contrast, Strategy A gives 80% more return than Buy-and-Hold (\$680

Table F.1
Performance summary of NDX-100 LSTM strategies.

Year	B&H		Training period								
	NDX	B	1Y			6M			3M		
			CO	CC	OC	CO	CC	OC	CO	CC	OC
Annual return											
max	55.7	35.0	42.3	45.1	25.8	42.7	45.1	18.0	35.0	42.6	20.7
min	-81.3	-14.1	-23.0	-34.7	-43.7	-21.3	-30.7	-30.5	-14.1	-32.0	-51.3
M	14.7	11.3	13.8	12.6	1.1	12.1	13.3	3.9	11.3	11.2	-0.2
μ	9.6	11.3	10.2	10.2	1.3	10.3	12.0	0.1	11.3	8.8	-2.1
σ	33.0	12.3	14.5	19.6	13.7	15.0	21.4	13.0	12.3	21.4	14.9
Maximum Drawdown											
max	-58.4	-27.4	-27.4	-48.5	-43.6	-27.4	-36.5	-34.1	-27.4	-45.2	-51.4
min	-5.1	-1.6	-0.9	-1.8	-1.1	-2.1	-5.1	-4.4	-1.6	-5.1	-2.7
M	-13.9	-5.6	-6.2	-11.5	-11.6	-5.9	-11.4	-10.6	-5.6	-11.4	-10.9
μ	-20.0	-7.5	-8.9	-14.6	-12.9	-8.5	-14.9	-12.7	-7.5	-15.1	-13.6
σ	14.9	5.6	6.7	10.2	8.0	6.7	8.6	6.6	5.6	9.3	9.6
Volatility											
max	65.2	24.6	24.8	53.6	39.3	24.6	44.9	36.6	24.6	40.5	36.3
min	10.3	5.2	1.7	5.9	2.0	4.9	9.8	8.1	5.2	9.7	6.9
M	18.2	9.0	9.9	16.2	13.5	8.9	15.1	12.8	9.0	14.4	12.5
μ	24.1	10.0	10.9	18.2	14.4	10.6	17.3	14.1	10.0	16.9	13.7
σ	13.7	4.6	5.7	9.7	7.1	5.2	7.9	6.1	4.6	7.5	6.2
Sharp Ratio											
max	3.1	3.7	3.5	3.0	1.9	3.7	3.1	1.4	3.7	2.7	1.5
min	-1.2	-1.4	-1.6	-0.9	-1.7	-1.4	-1.6	-1.4	-1.4	-2.0	-2.0
M	0.9	1.1	1.2	0.8	0.1	1.1	1.0	0.3	1.1	0.8	0.0
μ	0.9	1.2	1.1	0.8	0.2	1.2	0.8	0.1	1.2	0.6	-0.1
σ	1.3	1.2	1.3	1.1	0.9	1.4	1.4	0.8	1.2	1.3	0.9

Strategy B: 3-Month CO (“overnight”).

vs. \$379), with about 144 transactions per year on average. This means that for S&P we would need to trade every two days, whereas for Nasdaq, we would trade only once or twice a month.

Data availability

All the relevant data, Python code for analysis, detailed annual tables, and graphs are available via: https://github.com/XiangZhang-zx/SP_Nasdaq_Price_Movement_Prediction.

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