ARTICLE IN PRESS

Finance Research Letters xxx (xxxx) xxx

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

LSTM forecasting foreign exchange rates using limit order book

Katsuki Ito [a], Hitoshi Iima [b], Yoshihiro Kitamura [c,*]

[a] *Information Science, Kyoto Institute of Technology, Kyoto, Japan*
[b] *Information and Human Sciences, Kyoto Institute of Technology, Kyoto, Japan*
[c] *School of Social Sciences, Waseda University, Tokyo, Japan*

A R T I C L E I N F O

Keywords:
foreign exchange rate
limit order
LSTM

A B S T R A C T

We use long and short term memory (LSTM) to predict intraday returns in foreign exchange markets. As predictors, we use events in the limit order book. Compared to other models, our model predicts the movement of a 1-min midquote return. When we consider the bid-ask spread, this prediction does not bring economic gains. This result indicates that these events can contribute to price discovery and the studied markets efficiently set the spread.

1. Introduction

We examine whether events in the limit order book (LOB), limit orders, and transactions can predict intraday returns in foreign exchange (FX) markets. Extant studies for both the order- and quote-driven markets have highlighted the role of transactions (market orders) because informed traders supposedly exploit their informational advantage to trade with uninformed traders and therefore pay little attention to limit orders (e.g., Kyle, 1985; Easley et al., 1996). They assume that good private information motivates informed traders to buy an asset before price discovery occurs. Therefore, net buyer-initiated trade can predict future price movements. Notably, our finding can challenge this assumption: limit orders without trade can also discover a price.

Empirically, there are conflicting views on our research question. Kozhan and Salmon, 2012 concluded that information contained in an LOB did not add significant economic value out of the sample in their FX market. Brogaard et al. (2019) found that price discovery occurs predominantly via the LOB in their stock markets.

To address this issue, we use long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) to predict intraday returns in our eight FX rate markets. LSTM can consider the nonlinearity of current and past information for a prediction. Berger et al. (2008), who used the same data source as ours, found a non-linear relationship between order flows (net buyer-initiated trade) and 1-min FX returns in their FX markets, which motivated us to use LSTM.

Recently, LSTM has attracted considerable attention from financial economists because of its predictive power. There are several applications for asset price prediction: the SSE 50 stocks (Zhang et al., 2021), S&P 500 stocks (Fischer and Krauss, 2018), and Bitcoin (Chen et al., 2021). They mainly adopt current and past prices and liquidity variables (e.g., trading volume) as inputs for LSTM. Additionally, Zhang et al. (2021) showed that the LSTM with “buzz” stocks on the internet (online investor attention) outperforms their other models.

Our novelty is to adopt limit orders to which researchers have paid less attention predicting returns. In their seminal paper, Evans and Lyons (2002) developed a model in which the FX rate discovers its new equilibrium via order flows. In turn, researchers considered that limit orders convey no information to an FX rate and, therefore, that these orders do not predict future FX rates.

* Corresponding author:
E-mail address: kitamura@waseda.jp (Y. Kitamura).

https://doi.org/10.1016/j.frl.2021.102517
Received 22 January 2021; Received in revised form 3 October 2021; Accepted 19 October 2021
Available online 26 October 2021
1544-6123/

Our main findings are as follows. First, our findings support the contribution of limit orders to price discovery in the studied FX market. When we add limit order behaviors to LSTM, it outperforms that using only transactions. Additionally, the LSTM with LOB events outperformed the other models (e.g., momentum strategy, ordered logit) with the best accuracy. This indicates that limit orders, as well as transactions, can contribute to price discovery in the studied markets. Second, when we consider the bid-ask spread, the LSTM prediction does not bring tangible economic gains. The second finding is consistent with market efficiency in that information from the LOB does not bring economic gain.

2. Data and method

2.1. Data

We purchased Electronic Broking Services (EBS) data mine 2.0. The sample period ranges from October 1, 2018, to November 29, 2019. The EBS is an electronic broking system that has dominant shares in the deal of interbank markets for EURUSD and USDJPY rates. The original data record the events that occur on each bid and ask sides of the LOB at a frequency of 100 ms. The depth of the LOB on each side is ten.

2.2. Method

We use the LSTM model. Intuitively, the LSTM is a large nonlinear time-series model. Zhang et al. (2021) and Chen and Ge (2019) graphically explain the LSTM.

We consider the following variables as predictors of intraday returns: 1) improving order, 2) worsening cancel, 3) order placement at the best bid and ask (BBA), 4) cancel at the BBA, 5) order 1 tick from the BBA, 6) cancel 1 tick from the BBA, 7) Order > 1 tick from the BBA, 8) Cancel > 1 tick from the BBA. Here, one tick refers to one rank in the limit order. For a transaction, we consider the following three types: 9) trade inside the BBA, 10) trade on the BBA, and 11) outside of the BBA. The first type occurs inside the BBA, and the rest occur on/outside the BBA. All the event variables take +1 (-1) when their directions match the appreciation (depreciation) of the base (left-hand) currency. They take 0 when there are no events. Throughout this paper, x_i (i=1…11) refers to above the ith variable (e.g., x_1 is improving order).

We aggregate the original data frequency into 1–3-min ones and predict the intraday return of these frequencies. We predict the return of the eight FX rates: AUDUSD, EURCHF, EURJPY, SAUUSD, USDCHF, EURUSD, USDCNH, and USDJPY.

For the predicted variable, we split returns into the increase (appreciation of the base currency), decrease (depreciation of that), and no change groups in the full sample of each FX rate. We assign returns in these groups to +1, -1, and 0, respectively. Finally, we adopt the LSTM model for the prediction. For training, we use the first four-fifths of the full sample. We use the remainder for the test (out-of-sample prediction).

Table 1 shows the sample sizes (full sample, training, and out-of-sample). Table 2 shows the ratios of the predicted variables (+1, -1, and 0) in the test data for each FX rate and data frequency. Table 3 shows the correlation coefficients between each predictor and the return. Almost all the correlation coefficients are close to zero, and this indicates that a simple linear model with these predictors would poorly perform. Table A1 in the online appendix presents additional summary statistics to those in Table 3.

We describe our recurrent neural network, LSTM, for predicting the direction of change in the FX rate. The input into the recurrent neural network is based on an 11-dimensional feature vector $X_t = (x_{t1}, x_{t2}, \ldots, x_{t11})^{\mathrm{T}}$ where T is a transpose. The symbol $t(\geq 1)$is time, and its unit is n when n-min data frequency is used. This feature vector X_t consists of the numbers of various transactions, limit orders, and limit order cancelations that have occurred between time $t-1$ and time t, that is, during the last n min. Specifically, the input data are the above 11 variables 1)-11). The latest L feature vectors $X_{t-L+1}, X_{t-L+2}, \ldots, X_t$ are input into the recurrent neural network. In other words, the input vector is$x_t = (X^{\mathrm{T}}{}_{t-L+1}, X^{\mathrm{T}}{}_{t-L+2}, \ldots, X^{\mathrm{T}}{}_{t})^{\mathrm{T}}$, and the recurrent neural network predicts the FX rate at time t. We set $L = 10$.

The recurrent neural network uses 50 LSTM blocks as the hidden layer, and we adopt one hidden layer. Each LSTM block has one output, and therefore the hidden layer has 50 outputs. The output layer is fully connected. Its output vector $y_{t+1} = (y_{t+1,1}, y_{t+1,2}, y_t$

Table 1
Sample sizes

	1 min.			2 min.			3 min.		
	Full	Training	Out-of-sample	Full	Training	Out-of-sample	Full	Training	Out-of-sample
AUDUSD	282893	226314	56579	140396	112316	28080	92854	74283	18571
EURCHF	295570	236456	59114	146747	117397	29350	97074	77659	19415
EURJPY	295612	236489	59123	146764	117411	29353	97084	77667	19417
SAUUSD	282014	225611	56403	139970	111976	27994	92594	74075	18519
USDCHF	295616	236492	59124	146765	117412	29353	97085	77668	19417
EURUSD	430114	344091	86023	213422	170737	42685	141182	112945	28237
USDCNH	429970	343976	85994	213413	170730	42683	141173	112938	28235
USDJPY	430044	344035	86009	213423	170738	42685	141183	112946	28237

Note: Each min. refers to the data frequency. Numbers in "Training" and "Out-of-sample" are the sample sizes of data used for LSTM training and prediction, respectively.

Table 2
The ratios of the predicted values

FX rate	1 min. ratio of +1	ratio of -1	ratio of 0	2 min. ratio of +1	ratio of -1	ratio of 0	3min. ratio of +1	ratio of -1	ratio of 0
AUDUSD	0.372	0.363	0.265	0.407	0.401	0.192	0.429	0.418	0.153
EURCHF	0.346	0.342	0.313	0.390	0.384	0.225	0.416	0.410	0.175
EURJPY	0.411	0.406	0.183	0.439	0.434	0.127	0.458	0.448	0.094
SAUUSD	0.420	0.420	0.160	0.448	0.441	0.111	0.460	0.451	0.089
USDCHF	0.342	0.343	0.314	0.385	0.383	0.232	0.410	0.408	0.182
EURUSD	0.371	0.367	0.262	0.411	0.407	0.182	0.429	0.428	0.143
USDCNH	0.418	0.420	0.162	0.444	0.449	0.106	0.456	0.462	0.083
USDJPY	0.389	0.387	0.224	0.426	0.419	0.155	0.445	0.437	0.119

Note: Numbers are ratios of predicted variables (+1, -1, and 0) in the test data of each currency. Each min. refers to data frequency.

$_{+1,3})^{\mathrm{T}}$ is expressed as a trinary classification into increase, decrease, and no change in predicting the direction of change of a FX rate every n min. Each element of y_{t+1} is given by

$$y_{t+1,i} = \frac{e^{-u_{t+1,i}}}{\sum_{j=1}^{3} e^{-u_{t+1,j}}}, \tag{1}$$

$$\left(u_{t+1,1},\ u_{t+1,2},\ u_{t+1,3}\right)^{\mathrm{T}} = w^{\mathrm{T}} h_t + b, \tag{2}$$

where w is a weight vector, h_t is the output of the previous layer, and $b$is the bias vector. The right-hand side of (1) is a softmax function. LSTM predicts a positive signal (+1) if $y_{t+1,1} > y_{t+1,2}$ and $y_{t+1,1} > y_{t+1,3}$ and the negative signal (-1) if $y_{t+1,2} > y_{t+1,1}$ and $y_{t+1,2} > y_{t+1,3}$. Otherwise, it predicts zero. A positive (negative) signal means that the base currency appreciates (depreciates) and, therefore, is a signal of buying (selling) the base currency.

Adam is used as the optimizer to determine the values of learning parameters, such as w and b. In the optimizer, the loss function l_{t+1} is the cross-entropy, which is given by

$$l_{t+1} = -\sum_{i=1}^{3} a_{t+1,i} \ln y_{t+1,i}, \tag{3}$$

where $a_{t+1,i}$ is the correct answer for output $y_{t+1,i}$. The correct answer vector $(a_{t+1,1}, a_{t+1,2}, a_{t+1,3})$ is set as a one-hot vector. When the return belongs to the increase, decrease, and no change groups, $(a_{t+1,1}, a_{t+1,2}, a_{t+1,3}) = (1, 0, 0)$, $(0, 1, 0)$, and $(0, 0, 1)$, respectively.

3. Result

Before the details, we summarize our two main results in the following sentences.

First, we predict the midquote ((best bid + best ask)/2) returns with LSTM. The results show that the LSTM with all events of LOB (hereafter $\mathrm{LSTM}^{\mathrm{ALL}}$) outperforms the benchmark strategy to predict 1-min midquote return in seven of eight FX rates. In predicting 1-min midquote returns for all FX rates, $\mathrm{LSTM}^{\mathrm{ALL}}$ outperforms the ordered logit model and LSTM using transactions only. Second, we examine whether $\mathrm{LSTM}^{\mathrm{ALL}}$ makes a profit by considering the bid-ask spread. When $\mathrm{LSTM}^{\mathrm{ALL}}$ generates a positive signal, we buy the base currency at the best ask rate and sell it at the best bid in the next period. The case of the negative signal is reversed. As shown below, this does not bring about tangible economic gains.

As benchmarks, we adopt simple rules: momentum, reversal, and one-side bet strategies. Momentum (reversal) predicts the same (opposite) direction as the previous return. The one-side bet predicts only one direction (+1, 0, or -1) in the test data. For example, a one-side bet with +1 for the AUDUSD 1-min return has a 0.372 accuracy rate (see Table 2). Finally, as the benchmark, we select the strategy that has the highest accuracy rate in the test data and compare its performance with that of $\mathrm{LSTM}^{\mathrm{ALL}}$.

Table 4 shows the accuracy rate of the test data for each FX rate. The result of the benchmark appears in the "BM" column. The "OL" column shows the result of the ordered logit model with explanatory variables x_1…x_11. We estimate this model using training data and perform out-of-sample predictions. The "Order flow" column shows the result of LSTM with x_9, x_10, and x_11 only. LSTM with these variables is consistent with Berger et al. (2008), who find a non-linear relationship between order flows and 1-min FX rate returns in their EURUSD and USDJPY rate markets. The "All" column shows the result of $\mathrm{LSTM}^{\mathrm{ALL}}$ with all the inputs (x_1…x_11).

The bold numbers in Table 4 indicate the best accuracy. Table 4 shows that $\mathrm{LSTM}^{\mathrm{ALL}}$ performs relatively well in 1-min interval by 1%-3% and 1%-9% margins compared to benchmarks and the ordered logit model, respectively. LSTM has a nonlinear prediction ability and sufficiently captures multiple time dependencies (Lindemann et al., 2021), which is consistent with the results in Table 4. In turn, the LSTM with "Order flow" performs poorly. This indicates that limit order events can contribute to price discovery in the FX markets studied. This is consistent with findings in the stock market (Brogaard et al., 2019).

Extant literature considers that an asset price discovers private information via transactions of informed traders in stock (Easley et al., 1996) and FX markets (Evans and Lyons, 2002). Their models imply that only transaction variables (x_9, x_10, and x_11) can

Table 3
Correlation coefficient between each predictor and return.

	USDCHF			EURUSD			USDCNH			USDJPY		
	1 min.	2 min.	3 min.	1 min.	2 min.	3 min.	1 min.	2 min.	3 min.	1 min.	2 min.	3 min.
x_1	-0.0011	-0.0059	-0.0013	-0.0095	-0.0086	-0.0055	0.0076	-0.0034	-0.0045	-0.0130	-0.0107	-0.0100
x_2	-0.0074	-0.0033	-0.0076	-0.0107	-0.0068	-0.0106	0.0104	0.0109	0.0057	-0.0028	-0.0012	-0.0006
x_3	0.0177	0.0115	0.0109	0.0124	0.0096	0.0059	0.0173	0.0115	0.0088	0.0096	0.0054	0.0064
x_4	0.0066	0.0052	0.0054	0.0080	0.0050	0.0022	0.0018	-0.0037	-0.0040	0.0028	0.0036	0.0034
x_5	0.0091	0.0068	0.0060	0.0038	0.0038	0.0035	0.0042	0.0030	0.0010	0.0037	0.0010	-0.0002
x_6	0.0076	0.0105	0.0093	-0.0015	-0.0002	0.0012	-0.0042	-0.0083	-0.0070	0.0023	0.0039	0.0038
x_7	-0.0003	-0.0001	0.0029	0.0046	0.0038	0.0030	0.0078	0.0071	0.0070	0.0021	-0.0026	-0.0027
x_8	0.0053	0.0033	-0.0002	-0.0023	-0.0012	-0.0011	-0.0022	0.0000	0.0005	-0.0007	0.0019	0.0017
x_9	0.0045	0.0023	0.0000	-0.0052	-0.0026	-0.0011	0.0220	0.0156	0.0056	0.0040	0.0018	0.0002
x_10	0.0170	0.0138	0.0028	0.0062	0.0024	0.0084	0.0227	0.0164	0.0130	0.0112	0.0167	0.0080
x_11	0.0041	-0.0018	0.0026	0.0065	0.0046	0.0115	0.0040	-0.0025	-0.0035	-0.0096	-0.0066	-0.0139

Note: Each min. refers to the data frequency. Numbers are coefficients of correlation between each predictor and *the i* min return (i=1, 2, and 3). We calculate returns with log differences of midquote ((best bid + best ask)/2).

Table 4
Prediction results: accuracy rate

	1min. BM	OL	Order flow	All	Ret.	2min. BM	OL	Order flow	All	3min. BM	OL	Order flow	All
AUDUSD	0.392	0.375	0.373	**0.394**	1.102	0.407	0.408	0.409	**0.411**	0.429	**0.432**	0.428	**0.432**
EURCHF	0.424	0.341	0.407	**0.437**	1.029	0.413	0.383	0.401	**0.421**	0.416	0.411	0.420	**0.427**
EURJPY	0.412	0.421	0.411	**0.432**	1.099	0.439	**0.446**	0.439	0.445	0.458	**0.469**	0.459	0.465
SAUUSD	0.420	0.422	0.421	**0.430**	1.166	0.448	0.448	0.443	**0.452**	0.460	0.455	0.461	**0.464**
USDCHF	0.429	0.343	0.415	**0.434**	1.072	0.414	0.385	0.405	**0.418**	0.419	0.410	0.418	**0.424**
EURUSD	0.409	0.375	0.417	**0.430**	1.110	0.411	0.410	0.420	**0.429**	0.429	0.430	0.429	**0.437**
USDCNH	**0.471**	0.418	0.431	0.450	1.071	**0.465**	0.445	0.453	0.461	0.467	0.455	0.460	**0.472**
USDJPY	0.400	0.398	0.411	**0.425**	1.130	0.426	0.429	0.431	**0.438**	0.445	**0.453**	0.439	0.448

Note: Each min. refers to the data frequency. The number represents the accuracy rate in each model. The bold number indicates the best rate. Benchmark strategy "BM," ordered logit "OL," the LSTM with transaction variables (x_9, x_10, x_11) "Order flow," and the LSTM with all the inputs (x_1…x_11) "All." "Ret." is the return that the LSTM with all the inputs achieves. We calculate this using Equation (4).

predict FX returns. Our findings suggest that limit orders predict this. This implies that informed traders also use limit orders to maximize profits from their informational advantage (Kitamura, 2021).

To check the robustness of the predictive performance, we adopted different metrics for the model evaluation. Table A2 in the online appendix lists the mean F-scores for three predicted variables (+1, -1, and 0). This table also shows that $LSTM^{ALL}$ has a superior prediction ability.

To evaluate the performance of $LSTM^{ALL}$, we calculate investment return as follows:

$$\prod_{t=0}^{i}(1+r_{t+1}), \tag{4}$$

where $r_{t+1} = \ln q_{t+1} - \ln q_t (\ln q_t - \ln q_{t+1})$ when $LSTM^{ALL}$ predicts +1 (-1) at period t. q_t is a midquote and i is the number of timings in which $LSTM^{ALL}$ predicts non-zero.

The "Ret." column in Table 4 shows this evaluation (we report only for 1-min returns). The returns with Equation (4) are over one in all currency pairs. This indicates that trading with $LSTM^{ALL}$ can bring gains in the market in which there is no transaction cost.

The results in Table 4 motivate us to examine whether $LSTM^{ALL}$ prediction can bring tangible economic gains when we consider the transaction cost (bid-ask spread). To address this, we consider the following variable as the predicted variable: the variable takes +1 (-1) when the next bid (ask) rate at period t+1 is larger than the current ask (bid) rate at period t. Otherwise, this takes 0. With the same input variables of "All" in Table 4, we adopt the same procedure, and Table 5 shows this result.

In Table 5, we set a threshold. For each threshold, when the output value of LSTM for buy is maximal and exceeds the threshold, we buy the FX rate at the bid price and sell it at the ask price in the next 1-min period. With this rule, when $LSTM^{ALL}$ predicts +1 (-1), we calculate the return with $r_{t+1} = \ln bid_{t+1} - \ln ask_t (\ln ask_{t+1} - \ln bid_t)$. Finally, we evaluate these returns using Equation (4). We obtain the experimental results for various thresholds. Table A3 in the online appendix reports this experimental result. From this experiment, Table 5 reports the results for the three thresholds. The threshold 0 is a baseline, and 0.5 brings the highest return. The return for 0.4 is between those for 0 and 0.5. When the maximum value of the output exceeds the threshold, we conduct a transaction.

Compared with those in Table 4, almost all the returns in Table 5 are nearly 1. This indicates that $LSTM^{ALL}$ does not bring tangible gains once transaction costs are considered. We also confirm that $LSTM^{ALL}$ does not bring tangible gain at different frequencies (2 and 3 min) when we consider the spread (results are available upon request).

4. Conclusion

The LSTM model shows that the information of the LOB can predict 1-min midquote returns to some extent in the studied FX markets. Once we consider the bid-ask spread (transaction cost), our LSTM does not bring economic gains.

In addition to transactions, our findings suggest that limit orders can also contribute to price discovery in the studied FX market and, therefore, to the improvement of market efficiency. This finding helps market regulators monitor the LOB to understand market dynamics by focusing on limit orders. Although our LSTM model found the contribution of limit orders, it does not explain this contribution. Future theoretical studies should model their role in price discovery and show their economics. As such, machine learning models can create new jobs for economists.

CRediT authorship contribution statement

Katsuki Ito: Data curation, Formal analysis, Investigation, Methodology, Software, Writing – review & editing, Validation, Visualization. **Hitoshi Iima:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Writing – review & editing, Validation. **Yoshihiro Kitamura:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing.

Table 5
Returns with bid-ask spread at 1-min frequency.

Threshold	0	0.4	0.5
AUDUSD	0.998	0.998	1.000
EURCHF	0.999	1.000	1.000
EURJPY	0.992	0.995	1.001
SAUUSD	0.858	0.951	1.000
USDCHF	0.995	1.001	1.000
EURUSD	0.973	0.992	1.001
USDCNH	0.990	0.997	1.001
USDJPY	0.977	0.994	1.001

Note: When the output value of LSTM for buy is maximal and is over the threshold, we buy the FX rate at the bid price and sell it at the ask price in the next 1-min period. For sell, the case is the converse. Using bid and ask prices in each transaction, we calculate the return with Equation (4): The threshold 0 is a baseline, and 0.5 brings the highest return. The return for 0.4 is between those for 0 and 0.5.

Acknowledgements

We would like to thank the two anonymous reviewers for their suggestions and comments. This research is supported by the JSPS Grant-in-Aid for Scientific Research (grant numbers 19H01508 and 19K21704) and Grant-in-Aid from the Zengin Foundation for Studies on Economics and Finance.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2021.102517.

References

Berger, D.W., Chaboud, A.P., Chernenko, S.V., Howorka, E., JH Wright, J.H., 2008. Order flow and exchange rate dynamics in electronic brokerage system data. Journal of international Economics 75 (1), 93–109.
Brogaard, J., Hendershott, T., Riordan, R., 2019. Price discovery without trading: evidence from limit orders. Journal of Finance 74 (4), 1583–2143.
Chen, S., Ge, L., 2019. Exploring the attention mechanism in LSTM-based Hong Kong stock price movement prediction. Quantitative Finance 19, 1507–1515.
Chen, W., Xu, H., Jia, L., Gao, Y., 2021. Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants. International Journal of Forecasting 37 (1), 28–43.
Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J.B., 1996. Liquidity, information and infrequently traded stocks. Journal of Finance 51, 1405–1436.
Evans, M.D.D., Lyons, R.K., 2002. Order flow and exchange rate dynamics. Journal of Political Economy 110 (1), 170–180.
Fischer, T., Krauss, C., 2018. Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research 270 (2), 654–669.
Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural Computation 9 (8), 1735–1780.
Kitamura, Y., 2021. Price discovery via limit order in FX market (June 26, 2021). Available at SSRN: https://ssrn.com/abstract=3740392.
Kozhan, R., Salmon, M., 2012. The information content of a limit order book: The case of an FX market. Journal of Financial Markets 15 (1), 1–28.
Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53 (6), 1315–1336.
Lindemann, B., Müller, T., Vietz, H., Jazdi, N., Weyrich, M., 2021. A survey on long short-term memory networks for time series prediction. Procedia CIRP 99, 650–655.
Zhang, Y., Chu, G., Shen, D., 2021. The role of investor attention in predicting stock prices: The long short-term memory networks perspective. Finance Research Letters 38, 101484.