Equity Price Direction Prediction For Day Trading

Ensemble Classification Using Technical Analysis Indicators With Interaction Effects

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Abstract—We investigate the performance of complex trading rules in equity price direction prediction, over and above continuous-valued indicators and simple technical trading rules. Ten of the most popular technical analysis indicators are included in this research. We use Random Forest ensemble classifiers using minute-by-minute stock market data. Results show that our models have predictive power and yield better returns than the buy-and-hold strategy when disregarding transaction costs both in terms of number of stocks with profitable trades as well as overall returns. Moreover, our findings show that two-way and three-way combinations, i.e., complex trading rules, are important to "beat" the buy-and-hold strategy.

Keywords—day trading; equity price direction prediction; technical analysis; stock trading; ensemble classification; systematic trading; quantitative analysis; big data analytics.

I. INTRODUCTION

Stock-market predictability remains a widely debated topic. Reference [1] argued that any attempt to forecast future stock prices based on historic price information - technical analysis – may be unsuccessful. However, in the early 2000's, many economists and statisticians came to believe that stock markets are at least somewhat predictable based on technical analysis as well as certain fundamental valuation metrics [2]. This finding gave a boost to the research stream aimed at exploring market predictability by means of automated trading systems. Recent studies provide evidence for stock-market predictability [3] [4] [5] [6].

Stock price prediction based on technical analysis has become increasingly popular. Most studies using technical analysis make use of continuous-valued technical indicators as inputs to predictor models. This causes prediction models to make a classification based on the continuous values of these indicators, depriving trend information inherent in technical indicators [6]. In order to benefit from this additional knowledge, technical trading rules can be added to these conventional predictors (i.e., by creating interaction effects or complex trading rules). Various studies support the predictive power of technical trading rules [7] [8]. Evidence of improved predictive performance when adding simple technical trading rules to past returns is provided by [9].

In extant literature, we only found two previous studies, that take into account such complex trading strategies. Reference [10] has extracted prediction strategies for future price level estimation by using the optimum combination of technical indicators and concludes that combining multiple technical indicators improves the predictive performance compared to using a single indicator. Reference [11] studies the profitability of technical trading rules based on nine popular technical indicators and establishes several trading models based on two-way or three-way combinations. Reference [11] does not employ any classification algorithm and does not combine technical and indicators and trading rules into one model. As a result, we strongly believe that this research stream on complex trading rules should be explored more deeply.

Furthermore, we construct an integrated automated trading system that combines continuous-valued technical indicators, single technical trading rules as well as complex trading rules based on two-way and three-way combinations of individual indicators. Although most empirical studies are concerned with the statistical and economic performance of prediction models, we are also interested in whether a classification algorithm, such as Random Forest (RF), is able to better predict future stock price direction movements.

While many studies try to accurately predict future price levels, we focus on forecasting stock price direction. We investigate whether our proposed two-layered model trained on an eight-month sample of minute-by-minute S&P 100 data is able to generate profits. We hypothesize that a model based on a combination of technical indicator values with single and complex trading rules trained on intra-day data is able to predict future stock price direction accurately.

The remainder of the paper is structured as follows. In Section II, we explore related work in stock market prediction. Section III describes the methodology employed in this study. We describe our dataset and explain our different types of predictor variables

as well as our prediction model and the evaluation metrics. In Section IV, we discuss our results in terms of variable importance. Finally, Section V details our conclusions.

II. LITERATURE

When dealing with the complex, non-linear and dynamic behavior of financial markets the use of more sophisticated trading algorithms is necessary. In search for methods to address these weaknesses and thanks to the advances in computing and technology, research focuses on the various tools of computational intelligence. The most popular algorithms reported in literature are Logistic Regression, Neural Networks, K-Nearest Neighbors and Support Vector Machines [12]. Evidence of profitability of these trading algorithms is provided by numerous research articles [13] [14]. Among these machine learning techniques, Neural Networks have received the most attention.

An important development in machine learning is the use of ensemble models, which simultaneously combine different types of classifiers. For complex problems involving noisy inputs, it has been shown to be extremely challenging to obtain accurate results. The premise of ensemble classification methods is the observation that classifiers of different types and/or using different data exhibit distinct strengths and weaknesses, which has led to the belief that combining multiple classifiers can improve prediction accuracy [15]. While most studies use single classifiers for forecasting stock prices, ensemble classification methods such as Random Forest, AdaBoost and Kernel Factory remain largely unexplored [12].

Reference [6] compares four prediction models (RF, ANN, SVM and Naive-Bayes) and concludes that for continuous-valued data Random Forest outperforms the other three models, while it is ranked second in the case the algorithms are trained on trend-deterministic data. Reference [16] obtains better than random predictions when applying Random Forest on three different stock indices. Study [17], aimed at predicting the direction of daily change of the S&P CNF NIFTY INDEX, find that Random Forest performs better than Neural Networks, Logit Models and Discriminant Analysis in terms of hit ratio. Only Support Vector Machines (SVM) perform marginally better. While it is clear that both Random Forest and SVM achieve good results, no consensus is reached on which algorithm of the two performs best. In order to provide clarity on the matter, [12] carried out an extensive benchmark comparing seven machine learning techniques on yearly stock data. Their findings indicate that Random Forest is the top-performing algorithm. The proven superior performance of Random Forest makes it an excellent algorithm for use in this study.

A second recent observation in stock price prediction is the gradual shift from using daily, weekly, monthly or yearly entries to intra-day high frequency data for algorithmic learning. The main motivation in favor of intraday trading horizons is the notion of self-destruction of predictable patterns in stock prices [18]. This implies that predictability of stock returns is expected to weaken over time, as profitable trading strategies become known to the general public. Reference [19] finds that prediction models based on daily or longer data intervals for predicting future stock returns mostly underperform. Incited by the observed profits, traders unanimously start exploiting the profit opportunity, which in doing so, forces prices to adjust to new equilibria [20]. Similarly, [21] introduces the concept of the Adaptive Markets Hypothesis, arguing that arbitrage opportunities do exist from time to time, as profitable trading opportunities are exploited, they disappear. But at the same time, changing business conditions induce new profit opportunities that exist until they – too – eventually collapse.

Despite the relevance of intraday data among professional traders in practice, short-term stock price prediction is still largely under-represented in academic research [22]. Worth mentioning, however, are the contributions [10] [23] [24] [22]. These research articles commonly find evidence for intra-day market inefficiency, either totally or partially.

In order to fill the existing gap in literature, it is worthwhile to investigate the performance and profitability of Random Forest on intraday one-minute stock data.

III. METHODOLOGY

A. Approach

In our empirical analysis, we set out to examine whether the proposed model is capable of predicting future stock price movements and is able to translate this information into valuable buy/sell signals. We are mainly concerned with the profitability of the system. More specifically, we will investigate whether trading in accordance with the model predictions over a four-month period yields a positive return, disregarding transaction costs.

The developed model employs two different reasoning modules or architectural layers. We coin the first layer the Feature Engineering layer and the second layer the Prediction layer. The first layer derives a set of simple and complex trading rules from the input data. The output of the Feature Engineering layer consists of the discrete values 1, -1 or 0, representing buy, sell or hold signals, respectively. These signals serve as inputs to the Prediction layer, which employs Random Forest for feature learning and classification.

B. Data

For this study we gathered a one-year sample of minute-by-minute stock data extracted from Bloomberg. The use of intra-day high frequency data requires highly liquid equity markets. Therefore, we opt for stocks listed on the S&P100. The index consists of almost 45% of the market capitalization of the U.S. equity markets. The gathered data comprises the date and time, open-high-low-close price levels and the volume traded for each stock. The entire dataset covers the period from April 8, 2014 to April 14, 2015. Due to some irregularities in the extracted data, only 91 stocks of the original 100 are suitable for use. Furthermore, we employ a reduced dataset ranging from October 20, 2014 to April 14, 2015 for the following stocks: CMCSA, DD, DOW, HPQ, MDT, MET, NKE and GE. Lastly, ACT and CELG replaced APA and FCX in the S&P100 at the beginning of 2015. For the stock data to be consistent, historical prices and/or volume are adjusted to reflect spin-offs, stock splits/consolidations, stocks dividend/bonus and right offerings/entitlement. In this study, we use eight months for training (April 8, 2014 to December 5, 2014) and four months for testing (December 6, 2014 to April 14, 2015). For the reduced datasets, the training set comprises three months (October 20, 2014 – February 18, 2015) and the test set two months (February 19, 2015 – April 14, 2015).

C. Implementations

We used open-source R 3.2.1 using the parallel version of the randomForest package and RStudio as a modeling platform. Analyses required compute nodes of 512 GB RAM. Hence, the analysis is run on the Flemish Supercomputer featuring 16 of those big data HPC nodes.

D. Feature Engineering

Taking into account computational limitations, we selected ten popular technical indicators that have proven to be successful in predicting the direction of stock price movement in extant literature [25] [6] [26]. The ten indicators are: 1. Bollinger Bands (BB), Commodity Channel Index (CCI), Chaikin Accumulation/Distribution (ChaikinAD), Moving Average Convergence/Divergence (MACD), Relative Strength Index (RSI), Moving Average (MA), Weighted Moving Average (WMA), Stochastic Oscillator (Stoch), Triple Smoothed Exponential Oscillator (TRIX), Williams' %R (WPR). These same ten indicators are used for a similar by [25] and [6].

As previously mentioned in the Introduction Section of the paper, we employ a combination of continuous-valued indicators, single technical trading rules and complex trading rules as input variables to the prediction model.

D.1. Continuous-Valued Indicators

The continuous-valued indicators are calculated using the standard formulae presented. In order to prevent features with larger values from overwhelming those with smaller values, we standardize the obtained indicator values into new scores with mean zero and standard deviation one.

D.2. Single Technical Trading Rules

Number Trading rules give strict signals based on well-defined criteria for identifying market entry and exit points [27]. The Feature Selection layer of our model is in charge of devising such trading rules for each of the technical indicators employed in the study.

The first two technical indicators are moving averages (MA). The moving average crossover aims at detecting trend reversals, thereby generating buy and sell signals [28]. Two moving averages with differing lengths are plotted simultaneously. In this study, we set the moving average length for the short and long MA equal to ten and one hundred, respectively. A buy signal is triggered when the short moving average crosses the long moving average from below, while a sell signal is generated when the short moving average intersects the long moving average from above [29].

D.3. Complex Technical Trading Rules

Besides single technical trading rules, the Feature Selection layer also generates complex trading rules based on two-way and three-way indicator combinations. The main motivation for devising complex trading strategies is the observation that market analysts in practice do not rely on a single indicator for detecting trend reversals but rather combine the outcome of various technical indicators [30].

For combining multiple signals into a final buy/sell decision, we assign a larger weight to trade signals (buy or sell) than to hold signals. For instance, in case two indicators generate a hold signal and the third indicator a buy signal, the final decision is to buy. In case of multiple trade signals we employ majority voting for deriving the final outcome. Thus, when two indicators generate a sell signal and one indicator a buy signal, the final decision is in favor of selling. This way, we are able to model interactions between the various indicators.

In short, we employ ten technical indicators. This results in 18 continuous-valued indicators, 10 single technical trading rules, 45 two-way combinations and 120 three-way combinations. In total, the feature selection layer of our model consists of 193

predictors used as input to the Prediction layer of the developed model. All technical trading rules are transformed to binary variables.

D.4. Returns

As summarized in Section II numerous empirical studies provide evidence that classification algorithms are capable of beating the market. These results indicate that it may be possible to set up profitable trading strategies. Reference [16], for instance, constructed a trading system with break-even costs and finds the returns of the single day trading systems to exceed those of the random walk and contrarian investment strategies.

The trading strategy proposed in this study assumes a daily investment horizon. Profits and losses are determined per minute with no reinvestment and no trading positions are held overnight. Finally, we exclude the presence of transaction costs. The trading system works as follows: whenever a buy signal is triggered, the investor takes a long position in the respective share until a sell signal is generated, at which point the trader simultaneously sells and goes short. This position is held until the next buy signal or the end of the trading day, no positions are held overnight. In case the model generates two or more consecutive buy or sell signals, we focus on the first signal only, thereby ignoring subsequent signals.

The 193 predictors presented above (Sections 3.3.1-3.3.3), which constitute the independent variables, along with the return values, which form the dependent variable, serve as inputs to the prediction model.

E. Predictive Model

As discussed in the Data Section, the shares included in the S&P 100 index serve as input to the Feature Engineering layer, which is in charge of deriving continuous-valued indicators, single technical trading rules and complex trading rules yielding discrete buy, sell or hold signals. Subseqently, the returns are deterdined by applying the trading strategy to the generated signals. The predictors along with the return values are used for learning purposes. The ensemble algorithm identifies how stock market data and returns were related in the past and projects these insights to new data. The final classification decision of the ensemble algorithm is *one* or *zero*, indicating a positive or negative return, respectively. The Random Forest model discerns valuable signals from invaluable ones, thereby focusing on those trades expected to generate profit. Whenever the predicted probability on a positive return exceeds the cut-off value, we assume the investor will execute the respective trade. The overall return generated by the model is then calculated by adding up the returns of the performed trades. Besides the overall profitability of the strategy over a four-month period, we also compute the return per trade.

F. Model Assessment

As discussed in the Data Section, the shares included in the S&P 100 index serve as input to the Feature Engineering layer, which is in charge of deriving continuous-valued indicators, single technical trading rules and complex trading rules yielding discrete buy, sell or hold signals.

IV. RESULTS

Our results warrant the conclusion that complex trading rules seem to be more important than single trading rules. On average, two-way combinations add more than 15% to the accuracy (cfr. Fig. 1). Even more, adding a third rule increases the accuracy with almost 7% on top of the 15%.

Fig. 1: Average (RF) importance technical trading rules.
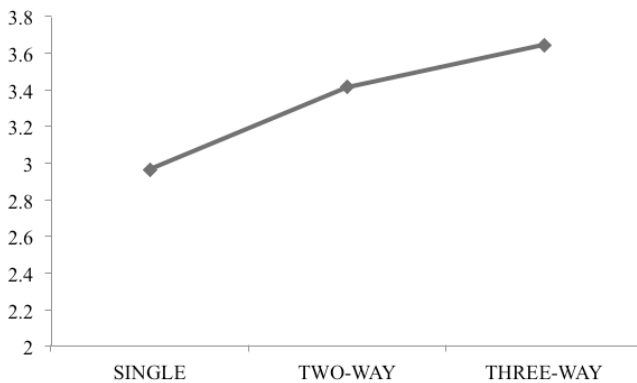
These findings are confirmed when we consider the average importance per indicator (Fig. 2). The mean decrease accuracy increases for two-way and three-way combinations. Interestingly, CHAIKIN, MACD, WPR and WMA clearly underform as single

technical trading rules but, on average, their importance increases when adding a second and a third trading rule. On average, CCI, STOCH, BB and its two-way and three-way combinations are among the trading rules that add most to the accuracy of our model.

Fig. 2 Average (RF) importance per technical indicator.
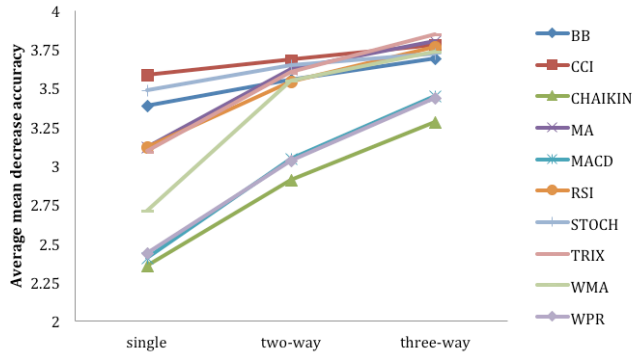
We find that five out of ten of the single technical trading rules are in the lower quartile (Fig. 3). The top quartile only consists of complex trading rules. Our findings show that combinations with MA, TRIX and RSI increased accuracy the most. We observe that combinations of these trading rules with the best performing rules from our ten indicator analysis (CCI, STOCH, BB) results in the largest mean decrease accuracy (Fig. 3). These findings confirm [11] as they conclude that the best models are based on combinations with RSI, MA, STOCH, OBV and MFI.

Fig. 3: Top ten technical trading rules
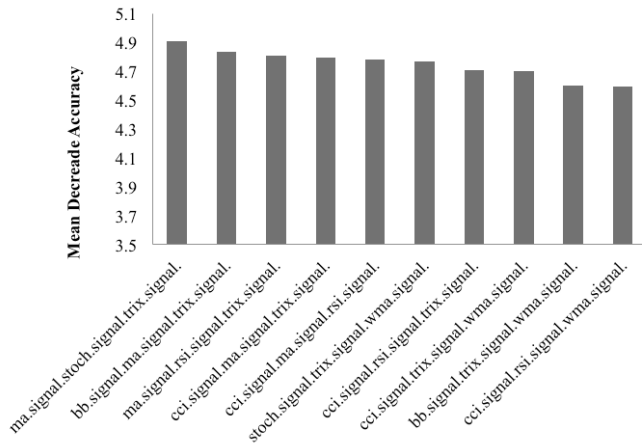
As can be observed from Fig. 4, the partial dependence plot for the relative time indicator (rel.time) shows that the largest probability for positive returns is during the opening of a trading day. This is in line with the findings by [31] indicating that traders are most active in the morning since they can benefit from the existence of high volatility. The partial dependence plot for RSI (value.rsi) demonstrates that normalized RSI values smaller than -1 have large log-odds for positive returns. By rescaling these values, we find that buying equity based solely on RSI values smaller than 39 results in an enhanced possibility of a positive return. Bollinger Band indicator (BB) consists of three values: lower Bollinger Band (lbb), upper Bollinger Band (ubb) and %B (pctB). Both lbb and ubb are relative since this allows us to compare between different stocks.[1] The lbb and ubb partial dependence plots are almost the exact opposite, which could be expected (Fig. 5). From the normalized lbb value of 0.5 we derive a relative lbb value of 0.99. As a consequence, from the moment the stock price crosses the lower Bollinger Band, prices are considered to be oversold. Traders are able to buy at cheap prices and generate a positive return [29]. Thus, we find a large possibility for positive returns for relative lbb values smaller than 0.99. The opposite is true for relative ubb values larger than 1.0003 (stock price crosses the upper Bollinger Band). As a result, promising buy-and-sell signals can be derived by using these Bollinger Bands.

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[1] These indicator values are divided by the stock price.

V. Conclusion

This study attempted to forecast intra-day stock price movement by combining continuous-valued technical indicators, single technical trading rules and complex technical trading rules. Random Forest was used as a prediction algorithm in our trading system.

Analyzing the importance of the different predictor variables resulted in interesting findings. It can be shown from the empirical results that continuous-valued technical indicators add most to the accuracy of our trading system. The variable indicating the relative time in a trading day is among the most important predictors, proving that the possibility of a positive return is largest during opening and closing of a trading day. Complex trading rules outperform single trading rules for both the five-indicator analysis and the ten-indicator analysis. Two-way and three-way combinations with moving average cross-overs and signals derived from a triple smoothed exponential oscillator yield the most important technical trading rules. Furthermore, these results are complemented by two trading signals with signals derived from the commodity channel index (CCI), stochastics (STOCH) and Bollinger Bands (BB) is preferable. Some single trading rules (RSI, WMA, WPR) performed badly but their importance sharply increased combined with other technical trading rules. The V-shaped partial dependence plots of the continuous-valued technical indicators suggest that extreme technical indicator values result in large log-odds of positive returns proving that both buying and selling based on these extreme values can yield positive returns.

As a future study, it would be interesting to employ different ensembles for this model. In particular, an important contribution to existing literature would be to use hybrid ensemble methods suchs as hybridEnsemble by [12] which consists of eight different sub-ensembles. Implementing transaction costs would be of further interest since it allows to better test the practicality of our model. Analyzing multiple parameter settings for the best performing technical indicators may be subject to another future research. Since our results show that many two-way and three-way combinations of technical trading rules have a higher mean decrease accuracy than the single trading rules, it would be interesting to further examine these effects in more detail.

Detailed results for each of the 91 stocks in our test period - reported in Table I - reveal that 50 of the 91 stocks result in overall profitable trades. This compares favorably to profitable trades in just 46 stocks in case of a buy-and-hold strategy, which barely outperforms the number of stocks resulting in losses (45 stocks). Hence, our active daytrading strategy clearly outperforms a buy-and-hold strategy when disregaring transactions costs. The same conclusion holds when aggregating total returns. Future research should investigate the risk/return trade-off of such automated trading systems.

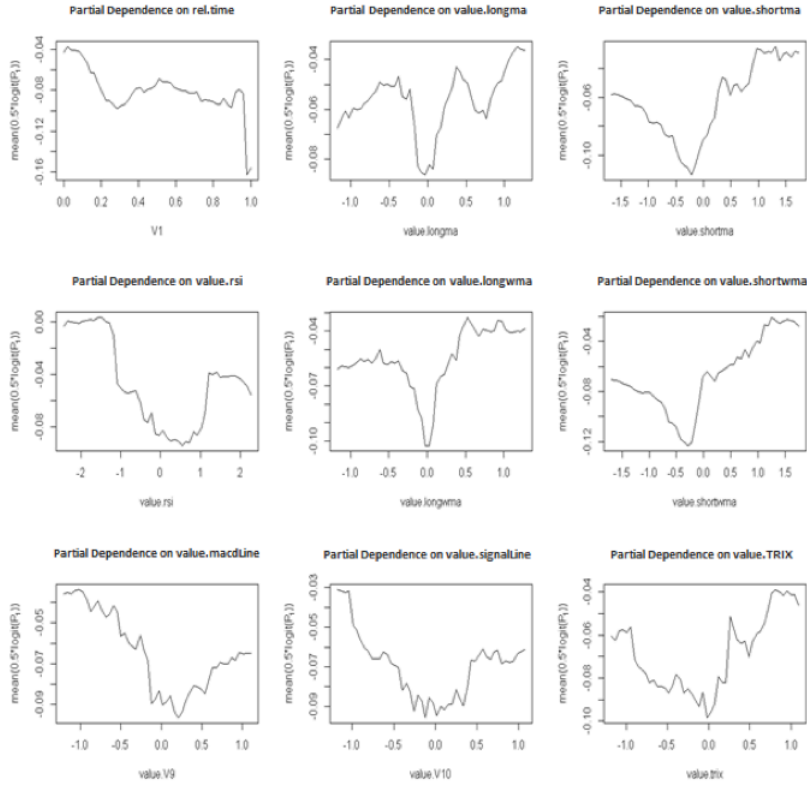## VI. Acknowledgements

Fig. 4. Partial dependence plots

Fig. 5. Partial dependence plots (continued)
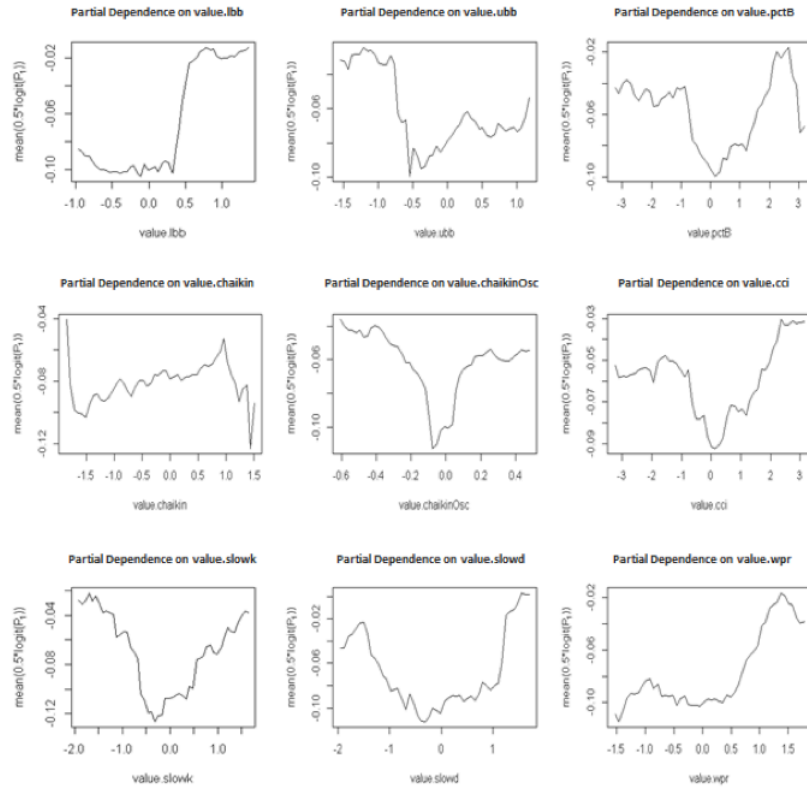
TABLE I.   OUT-OF-PERIOD RETURN PER INDIVIDUAL STOCK

Stock Symbol	Performance During Test Period		
	Total Return	*Return per Trade*	*Buy and Hold*
AAPL	-8.4712	-4.3691e-05	0.1130
ABT	9.1360	4.8343e-05	0.0282
ACN	9.8536	4.5642e-05	0.0941
ALL	10.0558	4.6721e-05	0.0397
AMGN	1.4179	7,4340e-06	-0.0386
AMZN	8.9485	4.3746e-05	0.2377
APA	131.9275	0.0011	-0.2641
APC	17.1767	7.5785e-05	0.1822
AXP	-13.2873	-6.2540e-05	-0.1421
BA	-8.0353	-4.5925e-05	0.1622
BAC	-2.6037	-1.2055e-05	-0.1022
BAX	6.3017	2.9071e-05	-0.0550
BK	-8.5147	-4.2879e-05	-0.0012
BMY	3.3800	1.5909e-05	0.0541
BRK	-6.9292	-3.6965e-05	-0.0523
C	-14.8417	-6.7881e-05	-0.0592
CAT	10.2735	4.9665e-05	-0.1562
CL	-1.2901	-1.5229e-05	0.0045
CMCSA	-1.2049	-5.8202e-06	0.0145
COF	-18.9057	-8.7664e-05	-0.0177
COP	2.3056	1.1420e-05	0.0204
COST	-4.9539	-2.4723e-05	0.0452
CSCO	23.9356	0.0001	0.0122
CVS	-0.0422	-2.0862e-07	0.1291
CVX	-10.4609	-5.7359e-05	-0.0070
DD	-2.0828	-2.4173e-05	-0.0492
DIS	7.6991	3.4963e-05	0.1367
DOW	5.2890	6.4946e-05	-0.0121
DVN	22.3812	0.0001	0.1309
EBAY	-6.4750	-2.9552e-05	0.0310
EMC	-9.2564	-5.1771e-05	-0.1353
EMR	-5.5484	-2.6092e-05	-0.0994
EXC	2.4181	1.2684e-05	-0.0625
F	-2.1043	-1.4004e-05	0.0204
FDX	-9.6838	-5.2802e-05	-0.0600
GD	9.9047	5.0435e-05	-0.0807

Stock Symbol	Performance During Test Period		
	Total Return	*Return per Trade*	*Buy and Hold*
GE	-2.6012	-3.8792e-05	0.1128
GILD	-7.9163	-3.9873e-05	-0.0281
GOOG	1.7446	8.9757e-06	0.0069
GS	-7.9760	-3.9603e-05	0.0153
HAL	1.2806	6.1907e-06	0.1681
HD	6.2555	2.9511e-05	0.1423
HON	-3.3235	-1.4900e-05	0.0375
HPQ	-8.3153	-9.9691e-05	-0.1486
IBM	-11.0979	-5.3722e-05	-0.0026
INTC	-5.9925	-2.8642e-05	-0.1609
JNJ	3.2924	1.5722e-05	-0.0734
JPM	5.2570	2.6950e-05	0.0069
KO	-1.6755	-8.4323e-06	-0.0681
LLY	0.7907	3.8127e-06	0.0196
LMT	5.0664	3.3093e-05	0.0388
LOW	-6.9480	-3.4645e-05	0.1388
MA	1.2431	5.3703e-06	-0.0004
MCD	5.1290	2.3994e-05	0.0461
MDLZ	-6.2289	-3.2497e-05	-0.0240
MDT	7.6992	9.1596e-05	0.0013
MET	7.1786	8.0801e-05	-0.0047
MMM	-4.1017	-1.7619e-05	0.0225
MO	6.7334	2.9772e-05	0.0196
MON	-6.2048	-3.1367e-05	-0.0126
MRK	8.4132	3.9788e-05	-0.0588
MS	-0.0803	-3.8819e-07	-0.0097
MSFT	-6.1670	-3.2983e-05	-0.1358
NKE	-0.7674	-8.2476e-06	0.0645
NSC	6.0510	2.9141e-05	-0.0538
ORCL	-7.0453	-3.7250e-05	0.0215
OXY	0.2869	1.3959e-06	0.0019
PEP	4.0925	2.0640e-05	-0.0147
PFE	10.1643	5.2088e-05	0.0974
PG	6.8492	3.1587e-05	-0.0755
PM	3.7389	1.8446e-05	-0.0996
QCOM	1.9296	9.2756e-06	-0.0570
RTN	1.9183	8.8121e-06	0.0069
SBUX	2.1135	9,7873e-06	0.1499

Stock Symbol	Performance During Test Period		
	Total Return	*Return per Trade*	*Buy and Hold*
SLB	3.7359	1.7165e-05	0.0375
SO	-1.4031	-7.7908e-06	-0.0713
SPG	-3.3037	-1.8092e-05	0.0532
T	14.1297	6.7957e-05	-0.0383
TGT	7.9454	3.9708e-05	0.1308
TWX	2.4896	1.2404e-05	0.0075
TXN	1.8117	1.0185e-05	0.0258
UNH	13.0347	6.0979e-05	0.1995
UNP	2.7729	1.2812e-05	-0.0834
UPS	7.0394	3.2834e-05	-0.1300
USB	-0.4845	-2.4533e-06	-0.0294
UTX	5.2334	2.3579e-05	0.0527
V	-0.3429	-1.7589e-06	-0.0072
VZ	1.3956	7.1296e-06	0.0107
WFC	-2.0247	-1.0364e-05	-0.0145
WMT	3.4717	1.7499e-05	-0.0483
XOM	-9.0434	-4.4238e-05	-0.0776

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