Exploring Trading Strategies Using Technical Indicators

ORIE 5252 – Quantitative Portfolio Management

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NOVEMBER 26, 2020

Table of Contents

Exploring Trading Strategies Using Technical Indicators 2

Technical Indicators 2

Methodology 3

  Data Source 4

  Factor (Technical Indicator) Analysis and Selection 4

    Factor Correlation Analysis 5

  Signal Creation 9

  Strategy and Backtesting 11

    Transaction Cost Model 11

    Risk Control and Portfolio Weights 12

    Strategy Backtest 13

Strategy Performance Analysis 15

Conclusion 16

References 18

Appendix 19

Exploring Trading Strategies Using Technical Indicators

Technical indicators have long been used as a method to develop alpha-generating trading strategies by predicting price movements. Unlike other factors which can be calculated from alternative data sources such as economic data or even news, technical indicators are derived from the historical prices and volumes of the underlying asset. Technical analysis attempts to capture market behavior, psychology, and sentiment through the study of price or volume trends and patterns. Technical analysis is mostly used on publicly traded stocks but can also be applied on other derivative products, such as futures or options.

This paper explores the application of such technical indicators in a daily trading strategy. The universe of stocks considered in this paper is limited to companies listed in the NASDAQ-100, the largest 100 non-financial companies listed on the Nasdaq stock exchange. The paper will cover the methodology of factor selection, signal creation, trading strategy development and strategy performance analysis.

Technical Indicators

There are many technical indicators used by traders and portfolio managers today. These technical indicators can be divided into four different classes: Momentum, Volume, Volatility, and Trend. There exist many indicators within each class. For example, average directional index (ADX), moving average (MA), and smart money index (SMI) are all classified as trend indicators. These indicators all attempt to quantify the relationship of the current price to its trend, albeit in different calculations and methods. To avoid redundancy and inter-factor correlation, only one indicator of each class should be used in a multi-indicator strategy. The full list of technical indicators considered and analyzed is shown below.

Momentum	Volume
Awesome Oscillator (AO)	Accumulation/Distribution Index (ADI)
Kaufman's Adaptive Moving Average (KAMA)	Chaikin Money Flow (CMF)
Price Percentage Oscillator (PPO)	Ease of Movement (EoM)
Relative Strength Index (RSI)	Force Index (FI)
Stochastic Oscillator (SO)	On-Balance Volume (OBV)

Volatility	Trend
Ulcer Index (UI)	Average Directional Movement Index (ADX)
Average True Range (ATR)	Commodity Channel Index (CCI)
Bollinger Bands (BB)	Detrended Price Oscillator (DPO)
Donchian Channel (DC)	Moving Average Convergence Divergence (MACD)
Keltner Channel (KC)	Mass Index (MI)

Table 1. List of All Considered Technical Indicators

The technical indicators selected above due to their popularity and usage by traders today. There are countless more other indicators that can also be considered but the examination of every single technical indicator is beyond the scope of this paper.

Methodology

The goal is to develop a profitable daily trading strategy utilizing a set of factors composed of technical indicators listed above. The universe of stocks utilized is composed by the companies in NASDAQ-100 index[1]. The benchmark index used to measure strategy performance is NASDAQ-100 (Ticker: ^NDX). An optimal combination of factors is determined through

[1] As of November 24, 2020

analysis of factor-factor and factor-target correlations. From the trade signals are derived from the selected factors, a trading strategy will be developed and backtested. A transaction cost model will be implemented to replicate real-world environments.

Data Source

The data required for the calculation are the open, high, low, close (OHLC) prices and volume for each stock. The data is downloaded from Yahoo Finance using a Python API and then cleaned and adjusted for dividends and splits. This paper conducts its calculations using data from 2010 to November 24, 2020. This time frame is separated into three periods:

- Training (In-Sample) Period: 2010 to 2015
- Test (Out-Sample) Period: 2016 to 2017
- Back Test Period: 2018 to 2020

Only data from stocks that have data for the entire time frame is used. Only 81 of the stocks from the NASDAQ-100 fulfill the conditions. The full stock list considered is shown in the appendix.

Factor (Technical Indicator) Analysis and Selection

The trading strategy to be developed utilizes a linear regression factor model to create signals. The factors for this model will be a set of 4 technical indicator. As explained before, to remove factor redundancy, only one technical indicator from each class of indicators will be chosen. Each of the four classes of indicators contains five technical indicators for consideration. The technical indicators are calculated for each stock given its OHLC and volume data (Padial, 2018)[2]. As many calculated indicators depend on the underlying price and volume, they cannot be directly compared between different stocks. A normalization process is applied by scaling each factor linearly to values between 0 and 1. This scaler will preserve the shape of the factor unlike other processes such as a normal (or standard normal) distribution mapping (Hale, 2019). Note that some technical indicators require a period of data before the evaluation date, thus null values will be present in some of the indicator calculations. Dates where there exist null values are dropped from consideration.

Factor Correlation Analysis

The target vector is composed the forward close-close 1-day returns, given that the strategy will be daily trading. The trading signal is developed by attempting to draw a relation between the proposed factors and the next-day return. Factors will be chosen based on their inter-factor and factor-target correlations. The goal here is to choose factors with the most correlation with the target factor, to maximize forecast predictability or explainability. Furthermore, to decrease redundancy and inter-factor correlations should be minimized. To determine these correlations on the entire universe of stocks, the calculated factor matrix and target vector for each stock is combined into one large dataset. Only the training data will be utilized for this correlation analysis. From the large dataset, a correlation is calculated. The table below shows the inter-factor correlations and factor-target correlations for the momentum technical indicator factors. The full matrix is 21 x 21, for the 20 factors and one target vector. The inter-factor

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[2] Calculation of factors utilize default parameters typically used. Accuracy of fit and performance of strategy will depend on these parameters to a certain degree but optimizing the parameters is out of the scope of this project.

correlations of the factors are relatively high, especially the correlation between AO and PPO or PPO and RSI. This justifies our rational for choosing one factor from each factor class.

	AO	KAMA	PPO	RSI	SO	Forward Returns
AO	1.0000	0.1412	0.6135	0.3563	0.3046	-0.0172
KAMA	0.1412	1.0000	0.0099	0.0231	-0.0309	-0.0174
PPO	0.6135	0.0099	1.0000	0.6102	0.3181	-0.0182
RSI	0.3563	0.0231	0.6102	1.0000	0.6531	-0.0294
SO	0.3046	-0.0309	0.3181	0.6531	1.0000	-0.0231
Forward Returns	-0.0172	-0.0174	-0.0182	-0.0294	-0.0231	1.0000

Table 2. Correlation Matrix of Momentum Factor Matrix and Target Vector

To analyze correlation, the following metrics are calculated for each factor combination: average inter-factor correlation, max inter-factor correlation, average factor-return correlation. The table below shows summary metrics for these calculations.

	Average Inter-Factor Correlation	Max Inter-Factor Correlation	Average Factor-Return Correlation
mean	0.2072	0.5609	0.01654
min	0.0323	0.0514	0.00622
max	0.6941	0.9250	0.02635

Table 3. Summary Metrics of Factor Correlation Analysis for Combinations Formed by Picking one from each Category

Minimizing inter-factor correlation is the main goal to reduce redundancy between factors. Some factor combinations show almost 70% correlation between factors, indicating significant redundancy and overlap in information provided by factors. A single factor alone does not demonstrate much correlation with the forward returns, with the max value being 2.64%. To select the optimal combination of factors, only combinations that have an average inter-factor correlation less than 0.05 and max inter-factor correlations under 0.15 are considered. The combination that has the highest average factor-return correlation in this set is KAMA, FI, DC, MI. The correlation matrix for this selected combination is shown below:

	KAMA	FI	DC	MI	Forward Returns
KAMA	1.0000	0.0219	-0.0083	0.0496	-0.0174
FI	0.0219	1.0000	0.0987	-0.0101	-0.0070
DC	-0.0083	0.0987	1.0000	-0.0220	-0.0297
MI	0.04960	-0.0101	-0.0220	1.0000	-0.0621
Forward Returns	-0.0174	-0.0070	-0.0297	-0.0621	1.0000

Table 4. Correlation Matrix of Selected Factors

This set of factors provided an average inter-factor correlation 0.0351, a max inter-factor correlation 0.0987 and average factor-target correlation of 0.0151. These will be selected factors for signal creation.

Selected Factors

1. **Momentum: Kaufman's Adaptive Moving Average (KAMA)**

   Kaufman's adaptive moving average was developed by Perry J. Kaufman in 1998 (Kaufman's Adaptive Moving Average (KAMA), n.d.). Unlike most other moving average indicators, KAMA measures not only price movement but also market volatility. Inclusion of market volatility filters out market noise and reduces false signals. KAMA is calculated using the following method:

$$\mathrm{KAMA}_i = \mathrm{KAMA}_{i-1} + \mathrm{SC} * (\mathrm{Close} - \mathrm{KAMA}_{i-1})$$

$$\text{Where:} \qquad \mathrm{KAMA}_0 = \mathrm{Close}_0$$

$$\text{Smoothing Constant: } \mathrm{SC}_i = \left(\mathrm{ER} * \left(\frac{2}{n_{fast}+1} - \frac{2}{n_{slow}+1}\right) + \frac{2}{n_{slow}+1}\right)^2$$

$$\text{Efficiency Ratio: } \mathrm{ER}_i = \frac{\left|\mathrm{Close}_i - \mathrm{Close}_{i+n_{ER}}\right|}{\sum_{j=0}^{10}\left|\mathrm{Close}_{i-j} - \mathrm{Close}_{i-j-1}\right|}$$

n_{slow}, n_{fast} are number of periods for the two exponential moving averages used in the smoothing constant. Typically, the values are 2 and 30, respectively. n_{ER} is the number of periods for the efficiency ratio, typically with a value of 10.

2. **Volume: Force Index (FI)**

The force index was developed by Alexander Elder in 1993 to measure the amount of force for price movement using close price and volume. The force index is an oscillator that fluctuate between positive or negative values, used to spot potential reversals. Spikes in force index usually confirm a breakout in price. The force index is calculated (typically a 13-day EMA is used) (Mitchell, 2019):

$$\text{Force Index}_i = \text{n-day EMA of } \left((\text{Close}_i - Close_{i-1}) * Volume\right)$$

3. **Volatility: Donchian Channel (DC)**

The Donchian channel is a channel indicator determined by three lines, developed by Richard Donchian (Chen, Donchian Channels Definition, 2020). The upper and lower band or line marks the highest and lowest prices of an asset over *N* number of periods, where *N* is typically 10. The middle band is a moving average of the close price. The specific indicator utilized is the percentage band, which quantifies the position in channel in a percentage value.

4. **Trend: Mass Index (MI)**

Mass index was developed by Donald Dorsey in the 1990s to examine the range between high and low values over a given time period (Chen, Investopedia, 2019). This indicator examines the narrowing and widening of these ranges and is used to identify potential market reversals. However, the mass index does not indicate the direction of the reversals. The mass index is calculated using the following equation:

$$\text{Mass Index} = \sum_{i=1}^{N} \frac{\text{n-day EMA of (High - Low)}}{\text{n-day EMA of a n-day EMA of (High - Low)}}$$

N is the calculation period, typically 25 trading days. *n* is the EMA period, typically 9 trading days.

Signal Creation

After dropping NA values from factor calculations, the data is separated into training, test, and backtest datasets. This provides 1470 dates of data for each symbol in the training (in-sample) dataset, 503 in the test (out-sample) dataset, and 730 in the backtest dataset. The combined large dataset of the in-sample data has dimensions 119070 × 4.

A trading strategy is built around signals. Typically, these signals are "buy" and "sell" decisions. A regression model fits the factors against the forward returns in attempts to utilize the factors to forecast the forward returns. There are many forms of regression models that can be utilized in this scenario. This study will utilize a simple linear regression model with an intercept coefficient included. Model regression fitting is performed on the in-sample data and model evaluation is performed on both the in-sample and out-sample data. The backtest data will be solely used for backtesting and will not be used in the model or strategy creation process. This allows recreation of real-world trading environments.

The linear regression can be explained with following equation, where forward return at time *t* for stock *i* is represented as a linear combination of the factors and the calculated coefficients showed in Table 5.

$$\text{Forward Return}_{t,i} = C_0 + C_1\,\text{KAMA}_{t,i} + C_2\,\text{FI}_{t,i} + \text{C}_3\,\text{DC}_{t,i} + \text{C}_4\,\text{MI}_{t,i}$$

The results of a linear regression fit are shown below:

	Coefficient	Standard Error	p-value
Intercept	0.002263	0.000292	0.0000
KAMA	− 0.002056	0.000334	0.0000
FI	− 0.000420	0.000338	0.2150
DC	− 0.001945	0.000193	0.0000
MI	− 0.000976	0.000441	0.0270

Table 5. Factor Linear Regression Model Results

R^2	0.00125
Standard Deviation of Forward Return	0.01978
Mean of Residuals	0.00000
Standard Deviation of Residuals	0.01976
$MSR_{Reduced}$ Residuals	0.00039

Table 6. In-Sample Model Metrics

Standard Deviation of Forward Return	0.01674
Mean of Residuals	0.00054
Standard Deviation of Residuals	0.01673
$MSR_{Reduced}$ Residuals	0.00028

Table 7. Out-Sample Model Metrics

The calculated coefficients all have negative correlation with the target forward returns. With the exception of force index (FI), the factors all have a significant p-value. The p-value measures the significance of the observed coefficients, representing the probability that such a coefficient is observed given the null hypothesis that the factor has no correlation with the target.

However, analysis of residuals shows a poor model fit. The R^2 value is 0.00125, imply that the factors have little explainability of the variation in forward returns. Furthermore, the standard deviation of residuals is approximately equal to the standard deviation of forward return values. The errors in the model are as almost as large as the variation in the target variable itself.

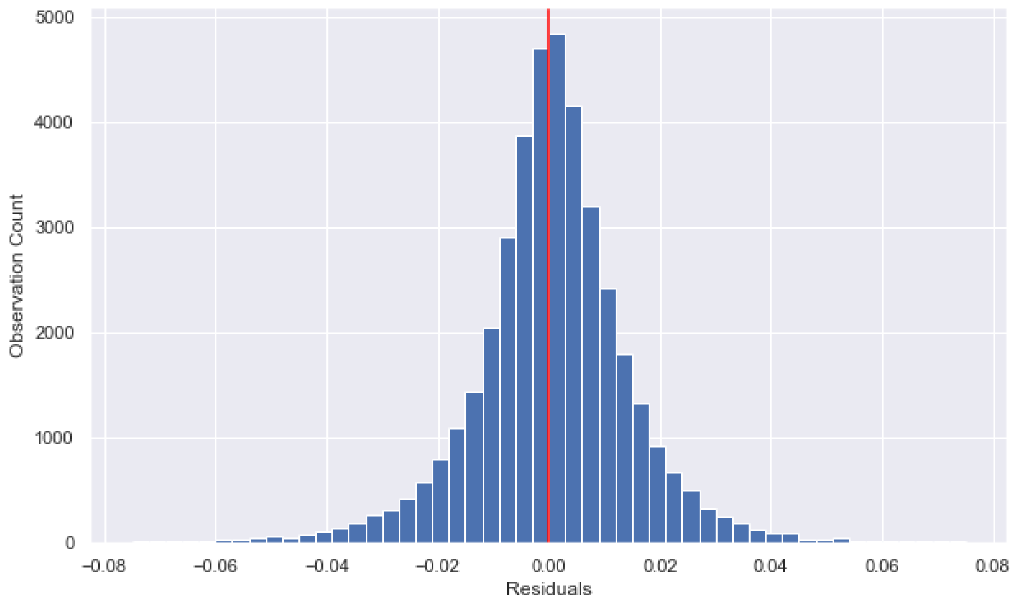

Figure 1. Histogram of Residuals

Examination of the histogram of residuals show that though there is significant variation or error, there is no bias in the error. This model will be utilized to create the signals, which are the forecast of forward returns given the factors.

Strategy and Backtesting

The daily trading strategy is a long-short strategy that works as follow. For each stock, if the stock has a positive forecasted forward return (a positive signal), the stock will be assigned a long position. If the stock has a negative signal, the stock will be assigned a short position. A transaction cost model and weighting model will be applied to each daily trade. The initial portfolio value of the strategy will be set at $100 million dollars.

Transaction Cost Model

To replicate real world trading scenarios in the backtest, a transaction cost model is utilized. The transaction cost per share traded, in dollars, for each stock is calculated:

$$TransactionCost = 0.004 * \sigma_{ann} * \frac{OrderSize}{MDV_{21}} * PreviousClosePrice$$

σ_{ann} is the annualized volatility in percent and MDV_{21} is the 21-day median traded volume. The order size is the change in position from the previous day. It is assumed that the costs equal for both buying and selling a stock.

Risk Control and Portfolio Weights

Several daily portfolio construction techniques are considered.

1. **Unweighted**: An equal dollar amount is allotted to each stock, long or short.
2. **Signal Strength Weighting**: Each trade amount is weighted by the strength of the signal. A larger forecasted forward return for a particular stock would result in a larger weight on that stock. The weight at time *t* for stock *i* is calculated:

$$\text{Weight}_{t,i} = \frac{\text{Signal}_{t,i}^2}{\sum_i \text{Weight}_t}$$

3. **Volatility Weighting**: To minimize risk or volatility, this method weighs each stock using its 21-day annualized volatility. Stocks with higher volatility will be assigned lower weights. This is calculated:

$$\text{Weight}_{t,i} = \frac{\text{Annual Volatility}_{t,i}^{-2}}{\sum_i \text{Weight}_t}$$

4. **Transaction Cost Weighting**: To reduce transaction costs, which is also a function of volatility, this method assigns stocks with higher transaction costs lower weights. This attempts to reduce trading costs as well as portfolio volatility. This weighting method is calculated using the transaction cost per dollar traded:

$$\text{Weight}_{t,i} = \frac{\text{Transaction Cost}_{t,i}^2}{\sum_i \text{Weight}_t}$$

Volatility weighting directly controls the risk of the portfolio by weighing less-volatile stocks with higher weights. Signal-weighting and transaction-cost weighting both also indirectly control risk as transaction costs and certain factors such as the Donchian channel are functions of the underlying asset's volatility as well. Another way risk is controlled is through usage of reasonably large stock universe. The diversification of the portfolio ensures reduction of non-systematic risk. However, the NASDAQ-100 may not necessarily be the best choice as financial companies are not included in the universe.

Strategy Backtest

The backtest is performed on the backtest dataset, which is unused in factor selection or model training. The time period for the backtest is 2018 to November 23, 2020. The figure below shows the change of portfolio value overtime for each of the four strategies as well as the performance of a buy-and-hold strategy with NDX, the NASDAQ-100 index.

Figure 2. Trading Strategy Backtest Portfolio Performance

The weighting model has a significant impact on the profitability of the strategy. The transaction-cost-weighted strategy performs significantly worse, suffering an overall loss. The volatility-weighted and unweighted model has a relatively similar performance, profitable but underperforming NDX. The signal-weighted strategy shows similar performance to NDX. Increasing weighting by signal does improve the strategy performance. For example, if the signal weighting scaler was increased from 2 to 10, the strategy would outperform NDX.

$$\text{Weight}_{t,i} = \frac{\text{Signal}_{t,i}^{10}}{\sum_i \text{Weight}_t}$$

Figure 3. Trading Strategy Backtest Portfolio Performance for Signal-Weighted Strategies

This performance increase by increased weighting on the strength signals implies that the signals do have a correlation with forward returns. The improved signal-weighted strategy outperforms NDX, more than doubling its profitability.

Strategy Performance Analysis

	Annualized Return	Annualized Volatility	Max Drawdown	Sharpe Ratio	Sortino Ratio
Unweighted Strategy	0.1200	0.1862	-0.1899	0.7020	1.0547
Signal Weighted Strategy	0.2058	0.2348	-0.2455	0.9149	1.3564
Volatility Weighted Strategy	0.1016	0.1709	-0.1706	0.6512	0.9991
Improved Signal Weighted Strategy	**0.4966**	**0.3048**	**-0.2463**	**1.4758**	**2.2741**
NDX	0.2320	0.2688	-0.2803	0.9114	1.2707

Table 8. Performance Metrics of Profitable Strategies

The improved signal-weighted strategy, with an amplified signal-weighting, outperforms all the other strategies and NDX significantly. Its annual return of almost 50% more than doubles NDX's annual return. Though the improved strategy does have higher annual volatility, its Sharpe and Sortino ratio, which measure the reward to risk, far outclasses the other strategies. The Sortino differs from the Sharpe ratio in that it does not penalize the strategy for positive volatility. Whereas the Sharpe ratio is calculated by annualized volatility divided by annualized volatility, the Sortino ratio divides instead by annualized downside volatility. Also, the maximum drawdown for the improved signal-weighted strategy is less than that for the NDX buy-hold strategy. Though all strategies suffered losses through the COVID-19 pandemic in early 2020, the improved signal strategy was rebounded faster. Note that the volatility weighted strategy does indeed have the lowest annual volatility, but it also has the lowest annual return and thus also the lowest Sharpe or Sortino ratios. Overall, an investment in the improved signal-weighted strategy would have tripled the initial investment of $100 million to $321 million over about three years.

All other strategies, including buying and holding NDX would not have even yielded over $200 million.

Conclusion

This exploration of creating a trading strategy using technical indicators as factors has provided some interesting insights. Despite the poor linear regression model results, the success of the backtest demonstrates that the signals or forecasted forward returns do provide meaningful prediction of the future returns. This is especially seen by the improved signal-weighted strategy. This paper covers the entire methodology of creating a trading strategy from scratch. There are many points within this methodology that could be improved upon.

1. **Factor (Feature) Selection**: The universe of factors can be expanded beyond the selected set of technical indicators used in this study. There exist many more indicators used by traders today. Furthermore, factors do not need to be limited to only technical factors. There have been many studies that utilize macroeconomic data, derivative products, or even alternative data such as weather or social media to create profitable trading strategies.
2. **Asset Universe Selection**: This study limits the universe of tradable assets to just companies within the NASDAQ-100 index. Further exploration to other sets of companies might provide more information and a better model.
3. **Signal Creation:** This model solely uses linear regression as the only method of creating signals from the selected factors, for simplicity. The relation between the factors and forward returns are most likely not linear, if such relation exists at all.

More sophisticated regression models such as polynomial regression, random forest, or neural networks might provide more accurate fits.

4. **Parameter Tuning (Optimization):** Both factor and weighting calculations utilized either default or arbitrary parameters. For example, the force index uses a 13-day exponential moving average. However, it may be that the calculation of shorter or long exponential moving average provides more correlation with forward returns. However, given the large number of parameters utilized by the models, the optimization of parameters will be a time consuming and a computationally taxing task.

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Appendix

ATVI	CTAS	INTU	PEP
ADBE	CSCO	ISRG	QCOM
ALXN	CTXS	KDP	REGN
ALGN	CTSH	KLAC	ROST
GOOGL	CMCSA	LRCX	SIRI
AMZN	CPRT	LBTYA	SWKS
AMGN	COST	LULU	SBUX
ADI	CSX	MAR	SNPS
ANSS	DXCM	MXIM	TMUS
AAPL	DLTR	MELI	TTWO
AMAT	EBAY	MCHP	TXN
ASML	EA	MU	TCOM
ADSK	EXC	MSFT	ULTA
ADP	EXPE	MDLZ	VRSN
BIDU	FAST	MNST	VRSK
BIIB	FISV	NTES	WBA
BKNG	GILD	NFLX	XEL
AVGO	IDXX	NVDA	XLNX
CDNS	ILMN	ORLY	
CERN	INCY	PCAR	
CHKP	INTC	PAYX	

Table A1. Tickers of Universe of Stocks Considered in the Strategy

	AO	KAMA	PPO	RSI	SO	ADI	CMF	EOM	FI	OBV	UI	ATR	BB	DC	KC	ADX	CCI	DPO	MACD	MI	FORWARD RETURNS
AO	1.000	0.141	0.614	0.356	0.305	0.031	0.209	-0.066	0.374	0.051	-0.487	-0.075	0.269	0.171	0.346	0.038	0.268	0.192	0.363	-0.051	-0.017
KAMA	0.141	1.000	0.010	0.023	-0.031	0.626	0.030	0.042	0.022	0.705	-0.052	0.811	0.007	-0.008	0.072	-0.015	0.060	-0.018	-0.049	0.050	-0.017
PPO	0.614	0.010	1.000	0.610	0.318	-0.012	0.319	-0.031	0.303	0.038	-0.731	-0.149	0.339	0.168	0.470	0.180	0.324	0.079	0.098	0.040	-0.018
RSI	0.356	0.023	0.610	1.000	0.653	0.040	0.577	0.041	0.150	0.090	-0.598	-0.075	0.868	0.741	0.823	0.205	0.782	-0.120	0.357	-0.020	-0.029
SO	0.305	-0.031	0.318	0.653	1.000	-0.029	0.429	0.050	0.130	0.008	-0.313	-0.080	0.700	0.604	0.592	0.132	0.648	-0.097	0.459	-0.046	-0.023
ADI	0.031	0.626	-0.012	0.040	-0.029	1.000	0.056	-0.055	-0.033	0.647	-0.058	0.493	0.027	0.024	0.071	0.014	0.035	-0.076	-0.071	0.010	-0.019
CMF	0.209	0.030	0.319	0.577	0.429	0.056	1.000	-0.016	0.087	0.061	-0.373	0.000	0.537	0.482	0.519	0.099	0.475	-0.101	0.257	-0.051	-0.022
EOM	-0.066	0.042	-0.031	0.041	0.050	-0.055	-0.016	1.000	0.232	0.022	0.048	0.072	0.038	0.026	0.037	0.051	0.125	-0.123	0.112	-0.064	0.003
FI	0.374	0.022	0.303	0.150	0.130	-0.033	0.087	0.232	1.000	-0.029	-0.167	-0.026	0.142	0.099	0.299	0.022	0.199	0.079	0.235	-0.010	-0.007
OBV	0.051	0.705	0.038	0.090	0.008	0.647	0.061	0.022	-0.029	1.000	-0.077	0.587	0.062	0.052	0.041	0.036	0.078	-0.109	-0.079	0.080	-0.017
UI	-0.487	-0.052	-0.731	-0.598	-0.313	-0.058	-0.373	0.048	-0.167	-0.077	1.000	0.183	-0.425	-0.229	-0.461	0.022	-0.391	-0.020	-0.202	0.189	0.022
ATR	-0.075	0.811	-0.149	-0.075	-0.080	0.493	0.000	0.072	-0.026	0.587	0.183	1.000	-0.057	-0.032	-0.004	0.000	-0.025	-0.087	-0.061	0.169	-0.004
BB	0.269	0.007	0.339	0.868	0.700	0.027	0.537	0.038	0.142	0.062	-0.425	-0.057	1.000	0.850	0.789	0.074	0.925	-0.133	0.419	-0.065	-0.027
DC	0.171	-0.008	0.168	0.741	0.604	0.024	0.482	0.026	0.099	0.052	-0.229	-0.032	0.850	1.000	0.659	0.051	0.732	-0.122	0.383	-0.022	-0.030
KC	0.346	0.072	0.470	0.823	0.592	0.071	0.519	0.037	0.299	0.041	-0.461	-0.004	0.789	0.659	1.000	0.095	0.785	-0.100	0.387	-0.021	-0.025
ADX	0.038	-0.015	0.180	0.205	0.132	0.014	0.099	0.051	0.022	0.036	0.022	0.000	0.074	0.051	0.095	1.000	0.062	0.009	-0.004	0.205	-0.001
CCI	0.268	0.060	0.324	0.782	0.648	0.035	0.475	0.125	0.199	0.078	-0.391	-0.025	0.925	0.732	0.785	0.062	1.000	-0.121	0.384	-0.066	-0.024
DPO	0.192	-0.018	0.079	-0.120	-0.097	-0.076	-0.101	-0.123	0.079	-0.109	-0.020	-0.087	-0.133	-0.122	-0.100	0.009	-0.121	1.000	-0.193	-0.006	0.000
MACD	0.363	-0.049	0.098	0.357	0.459	-0.071	0.257	0.112	0.235	-0.079	-0.202	-0.061	0.419	0.383	0.387	-0.004	0.384	-0.193	1.000	-0.087	-0.018
MI	-0.051	0.050	0.040	-0.020	-0.046	0.010	-0.051	-0.064	-0.010	0.080	0.189	0.169	-0.065	-0.022	-0.021	0.205	-0.066	-0.006	-0.087	1.000	0.006
FORWARD RETURNS	-0.017	-0.017	-0.018	-0.029	-0.023	-0.019	-0.022	0.003	-0.007	-0.017	0.022	-0.004	-0.027	-0.030	-0.025	-0.001	-0.024	0.000	-0.018	0.006	1.000

Table A2. Correlation Matrix of Considered Factors

Combo	Average Inter-Factor Correlation	Max Inter-Factor Correlation	Average Factor-Return Correlation
['KAMA', 'FI', 'DC', 'MI']	0.03510	0.09873	0.01507
['KAMA', 'FI', 'BB', 'MI']	0.04915	0.14203	0.01428
['KAMA', 'EoM', 'DC', 'MI']	0.03535	0.06384	0.01405
['KAMA', 'FI', 'DC', 'ADX']	0.03623	0.09873	0.01375
['KAMA', 'EoM', 'BB', 'MI']	0.04419	0.06452	0.01326
['KAMA', 'FI', 'BB', 'ADX']	0.04697	0.14203	0.01297
['KAMA', 'EoM', 'KC', 'MI']	0.04755	0.07219	0.01296
['KAMA', 'EoM', 'DC', 'ADX']	0.03231	0.05136	0.01273
['KAMA', 'EoM', 'BB', 'ADX']	0.03784	0.07404	0.01195
['KAMA', 'EoM', 'UI', 'ADX']	0.03838	0.05190	0.01070

Table A3. Factor Correlation Combination Analysis