A Primer on the Ichimoku Cloud Indicator

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We show that technical indicators engineered from the midpoint of high and low values over the short and medium timeframe have the predictive ability in the monthly cross-section of U.S. stocks. We use predictive regressions over 1967-2019 and t-statistics to test the null hypothesis that the indicators are not predictive. We find evidence that the Ichimoku cloud is highly predictive for short signals when the distance between the leading and lagging lines are below their median values in the previous day across all stocks. These excess returns hold for Fama and French 3 and 5 factors. These tests hold for additional sorts of the Ichimoku Cloud values in the lowest decile and quintile.

Keywords: technical analysis, Ichimoku Cloud, stock selection, short strategy

INTRODUCTION

We use an adaptation of the Ichimoku Cloud Indicator which is discussed in the book by Linton (2010) to generate excess returns in stock prices from monthly portfolios. The methodology we use is consistent with recent papers on moving averages that generate excess returns from both long and short portfolios in the cross section of stocks.

Linton (2010) outlines the Ichimoku Cloud to be the midpoint of high and low values of a set number of periods. Using 9 and 26 as standard parameters which line up with the Japanese calendar. Two of the main signals of the Ichimoku Cloud outlined in his book are the Turning Line and Standard Line. Linton (2010) discusses that a crossover between these signals can act like a moving average crossover.

Linton (2010) notes that cloud charts are composed of five lines: Turning Line (conversion line), Standard Line (Baseline), Cloud Span A (Cloud Span 1), Cloud Span B (Cloud Span 2), The Lagging Line (lagging span).

The turning line is a 9-day average between high and low. The standard line a 26-day average. The Cloud Span A is an average of these two lines and offset 26 periods. The Cloud Span B is a 52-period version of the formula. The lagging line is just the current close offset 26 bars prior. Using monthly data we do not have enough buy signals to create a long strategy using the turning line, standard line, or cloud span A or cloud span B. Therefore, we test a short only strategy using the turning line and standard line.

We generate a short signal when the distance between the 9 period turning line is farthest below the 26 period standard line. This is similar to a momentum strategy and outlined on a moving average study in Avramov et al. (2019).

This is similar to a momentum strategy where prices that are already low would push lower. Technical analysis application of momentum based studies were common in the 1960's and 1980's.

The review of Fama and Blume (1966) shows 15 of the 30 securities they considered seem to offer potential profits for the ½ of 1 percent filter rule over the period 1956-1962. When the 14 available securities from this group are examined over the later period 1970-1982 with a test with statistical confidence bounds, each of these securities gives highly significant profits for a floor trader; for example, an equally weighted portfolio gives profits of over 14 percent per year.

Richard J. Sweeney (1988) notes mechanical trading rules seem to have more potential than previous tests found. Fama and Blume (1966), looking at the Dow 30 of the late 1950s, found no profits for the best (1/2-percent) rule after adjusting for transaction costs.

LITERATURE REVIEW

The Ichimoku Cloud began to attract attention in the United States around the middle of the 2000s decade. Brian Dolan in Stocks, Futures and Options (2008) explained the basics of the cloud strategy and its history. Since Linton's book became a scarce commodity (out of print), it was listed on eBay for $250 in 2018, the Ichimoku Cloud has become one of the most popular technical analysis signals. It is hard to find a trading or charting platform that does not offer this tool. Academics, too, have noted the popularity of the trading signal. Lim, Yanyali and Savidge (2016) examine the effectiveness of the Ichimoku Cloud on 202 stocks on the Nikkei 225 and 446 stocks on the U.S. markets. Their study indicates that the cloud generates profitable signals, both long and short. The Ichimoku Cloud, by its design, makes it very easy to recognize long and short signals "at a glance."

Biglieri and Almeida (2018) examined the use of the Ichimoku Cloud for trading call options on Facebook. Again, the inherent design of the cloud system are extremely effective is recognizing short and/or long opportunities. Finally, Gurrib (2020) examined the use of the Ichimoku Cloud on trading the top ten energy stocks from the S&P Composite 1500 Energy Index. Again, the cloud strategy provided clear indications of long positions and short positions.

Menkhoff, Lukas, and Manfred Schlumberger (2013) states the use of technical analysis seems to be persistently profitable. In response to a positive test statistic, they note that personal and institutional risk restrictions limit the ability to fully exploit the theoretical profit potential. Thus arbitrage opportunity exists and the indicators are profitable.

Dai Min, et al (2016) show the optimal trading strategy is a trend following strategy. They show ex-ante experiments with market data reveals their strategy is efficient not only in the U.S. market (SP500 index) but also in the China market (SSE index). They observe an interesting divergence of the performances of the trend following trading strategy with short selling. Adding short-selling significantly improves the performance in simulations but the performance in tests using the market historical data is mixed.

Lo, Mamysky and Wang (2000) propose a systematic and automatic approach to technical pattern recognition using nonparametric kernel regression, and apply the method to a large number of U.S. stocks from 1962 to 1966 to evaluate the effectiveness of technical analysis. By comparing the unconditional the empirical distribution of daily stock returns to the conditional distribution – conditioned on specific technical indicators such as head-and-shoulders or double-bottoms, they find over the 31-year sample period, several technical indicators do provide incremental information and may have some practical value.

Blume, Lawrence, Easley, and O'hara (1999) show that volume provides information on information quality that cannot be deduced from the price statistic. They show that traders who use the information contained in market statistics do better than traders who do not. The technical analysis then arises as a natural component of the agents' learning process.

Zhu et al (2009) show how an investor might add value to an investment by using technical analysis, especially the MA if he follows a fixed allocation rule that invests a fixed portion of wealth into the stock market (as dictated by the random-walk theory of stock prices or by the popular mean-variance approach).

Han, Yufeng, Ke Yang, and Guofu Zhou (2013) document that an application of a moving average timing strategy of technical analysis to portfolios sorted by volatility generates investment timing portfolios that substantially outperform the buy and hold strategy. For high-volatility portfolios, the abnormal returns, relative to the capital asset pricing model (CAPM) and the Fama-French 3-factor models, are of great economic significance and are greater than those form the well-known momentum strategy.

DATA

We employ cross-sectionals using the center for research in security price data (CRSP). From 1963-2019. We use daily prices, high values, and low values for the NYSE/AMEX/NASDAQ stocks.

METHODOLOGY

We compute the Ichimoku Cloud for each stock and record the turning line and standard line values. We then compute the distance between the two values for each stock. We sort stocks into portfolios based on the distance between the turning line and standard line.

$$\text{TL}(9) = \frac{9\, period\ highest\ high + 9\, period\ lowest\ low}{2} \tag{1}$$

$$\text{SL}(26) = \frac{26\, period\ highest\ high + 26\, period\ lowest\ low}{2} \tag{2}$$

$$\text{TSD} = \frac{\text{TL}(9)}{\text{SL}(26)} \tag{3}$$

We take the distance between the two technical indicators. The short signal becomes $-1\ when\ TSD < (1-\sigma)\ below\ the\ median.$ This gives us the most extreme values. We also test the lowest quintile and lowest decile for robustness over 1967-2019.

We estimate monthly cross-sectional t statistics for 1967-2019 plugging in our short signal to the equation below.

$$\text{rm}_t = \alpha + \beta \text{x}_{t-1} + \epsilon_t \tag{4}$$

rm_t is the current period cross-sectional stock return and x_{t-1} is a dummy variable equal to -1. We estimate t statistics for signals related to bottom decile, lowest quintile and below median.

We also estimate Fama and French 3 Factors

$$\text{ri}_t - \text{rf}_t = \alpha + \beta_1 mktrf + \beta_2 smb + \beta_3 hml + \epsilon_t \tag{5}$$

Fama and French 5 Factors

$$\text{ri}_t - \text{rf}_t = \alpha + \beta_1 mktrf + \beta_2 smb + \beta_3 hml + \beta_4 rmw + \beta_5 cma + \epsilon_t \tag{6}$$

The two Fama and French models tell us whether the indicator is generating excess return by taking on excess risk by using factors to explain the returns. These tests all support the notion that the indicator for the Ichimoku cloud is both predictive and holds under the scrutiny of typical asset pricing tests without taking on excess risk.

We also do difference in mean testing, and Kolmgrov Simonoff tests. The difference in mean testing is simple and tells us whether the average return of our strategy is significantly higher than the buy and hold. The Kolmgrov Simonoff test tests whether the distribution of returns for the strategy comes from the same distribution of the population. This is tested in Lo Mamaysky and Wang (2000) as a test of technical indicator informativeness.

RESULTS

TABLE 1
RISK PREMIUM TEST

Signal	α	t	R2
Below Median	3.77	61.66	0.0017

The results from our t-test regression model show the indicators are indeed predictive of the next period returns although they have an extremely low R2. The R2 in Neeley et al (2013) for technical indicators suggests that ½ of 1% to be significant. Thus, 0.005 is the cutoff. We are well below this.

TABLE 2
FAMA AND FRENCH 3 FACTORS

Model R2 = 70.99%

Factor	Coef.	t
mktrf	-.80**	-31.74
smb	-.73**	-17.69
hml	-.66**	-17.74
α	2.05**	16.13

This model tells us that the returns have positive excess return and have a positive test statistic. This is showing that the market returns, size factor, and the value factor do not explain away the excess returns.

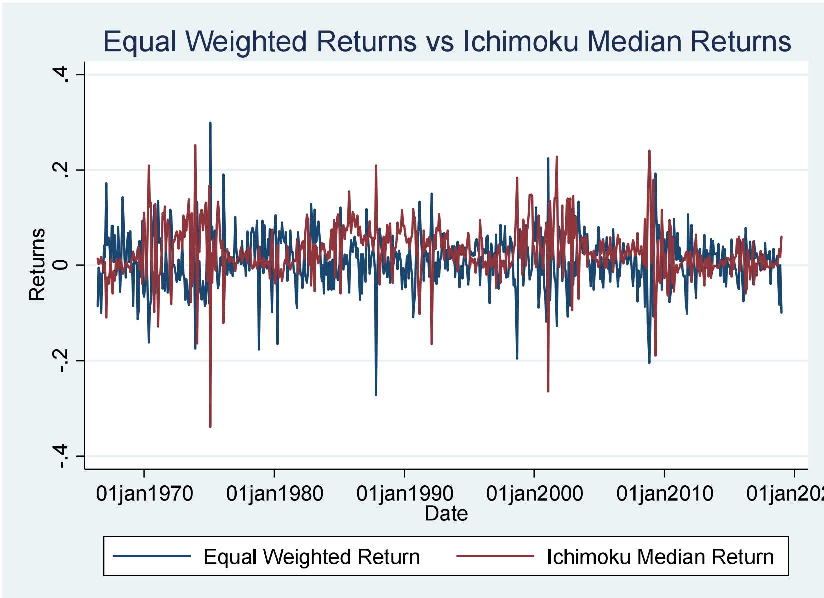
TABLE 3
FAMA AND FRENCH 5 FACTORS

Model R2 = 52.88%

Factor	Coef.	t
Mktrf	-.57**	-15.35
Smb	-.60**	-11.71
Hml	-.511**	-7.14
Rmw	.27**	3.80
Cma	.54**	5.07
α	2.70**	18.10

This model has a lower R2 but is still showing a positive alpha. Actually the alpha here is more positive than the previous 3 factor model.

FIGURE 1
DISTRIBUTION OF RETURNS



This shows the distribution of returns between the equal weighted portfolio and the Ichimoku Return. This shows that there are similar extreme values for the two portfolios.

DIFFERENCE IN MEANS TEST

We run two different tests. The first we test the difference in means between our strategy and the equal weighted returns from the center for research in security prices (CRSP).

Under the null hypothesis Ho: the mean difference = 0.
Under the alternative hypothesis Ha: the mean difference >0.

We test this for the active return (Ichimoku Median) vs the benchmark (Equal Weighted Return). Our time frame is 1967-2019

TABLE 4
SUMMARY STATISTICS

Variable	Obs	Mean	Std. Dev	Min	Max
Ichimoku	632	0.0288	0.5446	-0.2722	.2993
Equal Weighted	632	0.0107	0.5616	-.3399	.2522
T-Test:					
Ha: mean(diff) <0		Ha: mean(diff) != 0		Ha: mean(diff) >0	
Pr (T < t) = 1.0000		Pr(|T|>|t|) = 0.0000		Pr(T>t) = 0.0000	

t=4.3554 with 631 degrees of freedom.

This shows that the Ichimoku return is significantly higher than the equal weighted portfolio return. This it is a viable strategy.

The second test we run involves testing over all recession periods. Under the null hypothesis, when there is a recession (according to the Federal Reserve Bank of St. Louis 'FRED').

FIGURE 2
EQUAL WEIGHTED RETURN $1 INVESTMENT

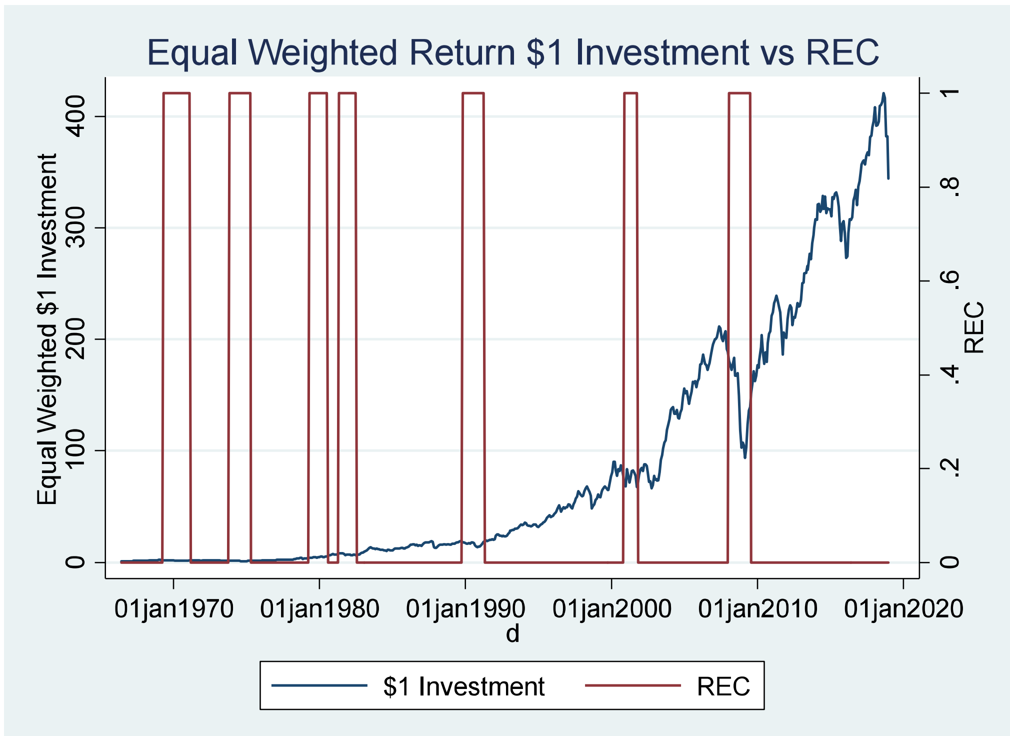


TABLE 5
RECESSION SUMMARY STATISTICS

Variable	Obs	Mean	Std. Dev	Min	Max
Ichimoku	117	0.0382	0.0874	-.3399	.2522
Equal Weighted	117	-0.0029	0.0809	-.2052	.2993

T-Test:

Ha: mean(diff) <0	Ha: mean(diff) != 0	Ha: mean(diff) >0
Pr (T < t) = 0.9962	Pr(|T|>|t|) = 0.0076	Pr(T>t) = 0.0038

t=2.7165 with 116 degrees of freedom.

This suggests that the short strategy involving the Ichimoku cloud is better in both recession only periods and all overall periods. It might suggest that the Ichimoku cloud should be considered as a viable technical indicator on the short side.

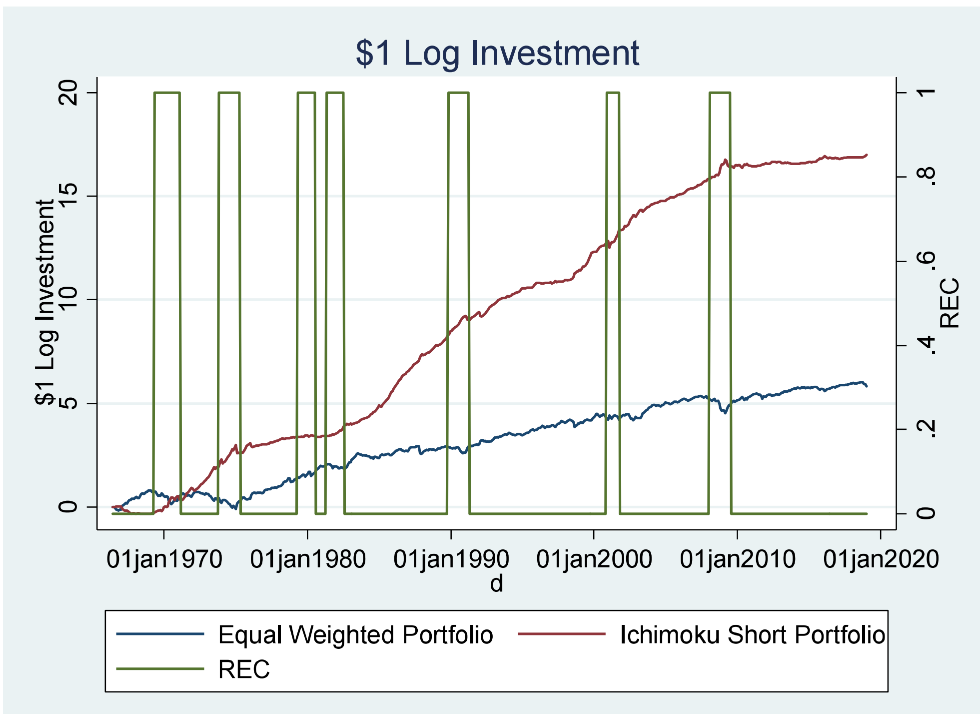
KOLMGROV SIMONOFF TEST

We use this test for equality of distributions. It is used in Lo, Mamaysky, and Wang (2000) to test for informational content surrounding the conditional returns on technical indicators compared to the unconditional returns. This can be used as a test of informational content. The test suggests that the data can be distinguished from the equal-weighted returns.

TABLE 6
KOLMGROV SIMONOFF

Smaller Group	*D*	P-value
Ichimoku:	1.2659	0.000
Cumulative:	-0.2993	0.000
Combined K-S:	1.2659	0.000

FIGURE 3
LOG GROWTH OF $1



ROBUSTNESS

We compare the below median strategy to the Ichimoku values sorted on deciles and quintiles for the Turning Line and Standard Line strategy. We show the results hold for these additional sorts. We analyze the time period 1963-2017.

TABLE 7
ROBUSTNESS CHECK

	Returns			**Buy Hold**	**Excess Returns**		
	d10	q5	m2	ewr	d10_	q5_	m2_
Return	148.44**	89.41**	30.22**	12.67**	134.95**	75.91**	17.69**
	(60.78)	(64.77)	(63.57)	(393.56)	(55.05)	(54.67)	(36.83)
(S.E.)	0.00	0.00	0.00	0.00	0.00	0.00	0.00

This table shows the annualized returns with t statistics in parentheses. The standard error for the test under the null hypothesis shows that the model is highly accurate. The d10 is the lowest decile, q5 is the lowest quintile, m2 is the below median. EWR is the equally weighted portfolio. We then use d10_, q5_, and m2_ for the excess returns of each portfolio for lowest decile, bottom quintile and below the median.

This tells us that the returns go up with the lower (more extreme values) for shorting. This is again consistent with a momentum based strategy or would support overreaction to extreme values.

We use traditional asset pricing methods of explaining the returns using the Capital Asset Pricing Model (CAPM), Fama and French (1993) 3 factor model, and the four and five factor models. We find that including momentum and the fifth factor do not explain away the returns at any decile. The excess returns are tested and annualized. The excess returns are percentages.

TABLE 8
CAPM MODEL

	D10	Q5	M2
Return	134.91**	75.93**	17.76**
	(54.66)	(54.32)	(36.73)
Market	0.50*	0.33*	0.04
	(1.72)	(1.71)	(0.83)

This table shows us the excess return to be positive and significant when being explained by the market return. We also see the market return is a significant factor in explaining the returns.

TABLE 9
3 FACTOR MODEL

	D10	Q5	M2
Return	130.30**	71.80**	15.96**
	(50.78)	(49.62)	(31.96)
Market	0.92**	0.67**	0.27**
	(4.09)	(5.23)	(5.93)
SMB	2.06**	1.59**	0.68**
	(6.27)	(8.54)	(10.03)
HML	2.95**	2.59**	1.72**
	(6.96)	(10.78)	(19.69)

This table shows us that the 3 factor model reduces the excess return some. All of the factors are significant in explaining the returns.

TABLE 10
4 FACTOR MODEL

	D10	Q5	M2
Alpha	129.30**	71.62**	15.88**
	(50.56)	(49.45)	(31.78)
B Mkt	0.65**	0.56**	0.21**
	(2.76)	(4.17)	(4.50)
B SMB	1.62**	1.41**	0.59**
	(4.62)	(7.12)	(8.22)
B HML	2.65**	2.46**	1.66**
	(6.13)	(10.09)	(18.54)
B Rmw	(2.23)**	(0.91)**	(0.46)**
	(-3.69)	(-2.65)	(-3.68)

This table shows us a further reduces excess return for the portfolios when including the momentum factor of the 4 factor model. All of the models are increasing in their alphas as they are greater in the distance of the turning line below the standard line.

TABLE 11
5 FACTOR MODEL

	D10	Q5	M2
Alpha	129.31**	71.65**	15.91**
	(50.56)	(49.46)	(31.83)
B Mkt	0.54**	0.34**	0.00
	(2.13)	(2.36)	(0.05)
B SMB	1.62**	1.43**	0.62**
	(4.65)	(7.21)	(8.59)
B HML	2.98**	3.09**	2.29**
	(6.02)	(11.02)	(22.58)
B Rmw	(2.18)**	(0.81)**	(0.38)**
	(-3.60)	(-2.37)	(-3.05)
B Cma	(1.00)**	(1.88)**	(1.95)**
	(-1.38)	(-4.54)	(13.21)

This table shows the five factor model and that the excess returns all still hold. Again the lowest decile produces the greatest return followed by the lowest quintile and below median.

We show the growth of a $1 investment in each of these portfolios in the figure below. We compare them to the equally weighted portfolio.

FIGURE 4
LOG GROWTH OF $1

CONCLUSION

We show that the Ichimoku cloud can predict negative equity premium in the market. Mainly by shorting stocks when the Tenkansen (turning line) is below the Kijunsen (standard line). We short stocks when the TSD is below its median values in the previous day. The results hold for the Fama and French 3 factor and 5 factor models. It also shows highly significant returns during recessions. We show that the returns are statistically greater than a buy-and-hold evidenced by t-statistics. It may be a useful indicator for similar momentum based and technical indicator studies. It would be interesting to extend this to daily analysis to see the different nuances in high and low values and the construction of the indicator.

The indicator has been studied increasingly as of lately and fits in to the resurgence of technical analysis studies. The Ichimoku cloud is of interest because of its increasing popularity among practitioners and on financial charting software. This paper shows that it can also be used for academic studies where momentum or moving average based indicators generate excess returns. Future work may include combining this indicator with other technical indicators and using machine learning to predict trading rules.

REFERENCES

Avramov, D., Kaplanski, G., & Subrahmanyam, A. (2019). *Anchoring on Past Fundamentals*. Available at SSRN.

Biglieri, J.V., & Almeida, L.G. (2018, May 14-16). Ichimoku Trend Predictions. Is It Working on Facebook? *Proceedings of the 5th International Conference "Modern Economics."* Vigo Spain.

Blume, L., Easley, D., & O'hara, M. (1994). Market statistics and technical analysis: The role of volume. *The Journal of Finance*, 49(1), 153-181.

Covel, M. (2009). *Trend following (updated edition): Learn to make millions in up or down markets*. FT Press.

Dai, M., Yang, Z., Zhang, Q., & Zhu, Q.J. (2016). *Optimal trend following trading rules*. Mathematics of Operations Research.

Dolan, B. (2008, March). *Trading with Clouds*. Stocks, Futures and Options.

Fama, E.F., & Blume, M.E. (1966). Filter rules and stock-market trading. *The Journal of Business*, 39(1), 226-241.

Gurrib, I. (2020, January 16). *Can the Leading US Energy Stock Prices Be Predicted Using Ichimoku Clouds?* Retrieved from https://ssrn.com/abstract=3520582 or http://dx.doi.org/10.2139/ssrn.3520582

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, 48(5), 1433-1461.

Lim, S., Yanyali, S., & Savidge, J. (2016). Do Ichimoku Cloud Charts Work and Do They Work Better in Japan? *IFTA Journal*.

Linton, D. (2010). *Cloud Charts*. Updata, London.

Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *The Journal of Finance*, 55(4), 1705-1770.

Menkhoff, L., & Schlumberger, M. (2013). Persistent profitability of technical analysis on foreign exchange markets? *PSL Quarterly Review*, 48, 193.

Neely, C. J., Rapach, D.E., Tu, J., & Zhou, G. (20114). Forecasting the equity risk premium: the role of technical indicators. *Management Science*, 60(7), 1772-1791.

Sweeney, R. J. (1988). Some new filter rule tests: Methods and results. *Journal of Financial and Quantitative Analysis*, 23(3), 285-300.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, 21(4), 1455-1508.

Zhu, Y., & Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, 92(3), 519-544.