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Ichimoku Cloud Forecasting Returns in the U.S.

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A B S T R A C T

Purpose: We show that the Ichimoku Cloud can forecast stock returns in the U.S., Canada, Germany, and U.K.
Design/methodology/approach: We use a regression of next months index return regressed on the Ichimoku Cloud entry signal for price crossing above 9 periods, 26 period, 52 periods and a crossover between 9 and 26 periods. The regression slope coefficient is recorded as the risk premium return. We also record the t-statistic and R^2 of the model. We note that T-statistics of 1.65 are statistically significant. R^2 is economically significant with a value above .5 percent.
Findings: This is showing real-time application how the current Ichimoku Cloud signal can predict tomorrow's stock return. The strongest results occur for lagged values one period in the U.S. which shows initial justification to using the Ichimoku Cloud. We additionally show the Ichimoku Cloud entry signals are strong in regards to T-statistics and R^2 when benchmarked on each of the equity markets in the U.S., Canada, Germany, and U.K.
Research limitation/implications: The model only considers technical indicators for forecasting risk premium and could benefit from additional indicators or macro fundamentals.
Originality/value: This is the first paper to use Ichimoku Cloud in the risk premium forecast framework.

Keywords: Technical Analysis, Risk Premium, Ichimoku

I. Introduction

We provide initial justification for using the Ichimoku Cloud in a risk premium forecast test. We provide the framework for testing, methodology, construction of the indicator and relate it to the moving average which is more common in literature.

The Ichimoku Cloud dates back to the turn of the 1900's. It is constructed best using candlestick charts which were used in trading on the Osaka rice exchange circa 1750. (Linton 2010). The documentation of the Ichimoku Cloud is from Munshis Homma who started trading on the exchanges from an inherited fortune. The use of the cloud was based on mass psychology much like technical analysis is in behavioral economics today[1].

Most of the Ichimoku Cloud construction is based on the midpoint of high and low over several look-back periods. They are 9, 26 and 52 and are noted to be the number of days in 2 Japanese trading weks, number of days in a Japanese trading month, and 2 months. The cloud is easier seen on a price chart

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1) Most of technical analysis is rooted in mass psychology and behavioral economics

with Japanese candlesticks. Nilson (1991) has a book on the Japanese Candlesticks and their construction.

We test summary statistics and initial results of the Ichimoku cloud. We compare the results to both recession and expansion periods. We then extend the sample to the entire U.S. stock market from 1988-2021. We compare the results from the U.S. to Canada, Germany and the U.K.

The construction of the Ichimoku cloud is noted below:

1. Turning Line - 9 period highest high and lowest low midpoints
2. Standard Line - 26 period highest high and lowest low midpoints
3. Cloud Span A - midpoint of 1. And 2. Shifted 26 periods forward
4. Cloud Span B - midpoint of high and low over 52 periods.
5. The Lagging Line - the current close offset 26 periods in the past.

The main entry signals are:

1. Lagging line crossing the cloud
2. Price crossing the cloud
3. Price and lagging line crossing the cloud
4. The cloud spans crossing
5. The turning linecrossing the standard line

We organize the paper in to two parts following the literature review and methodology. Part one denotes testing the risk premium in the U.S. from 1950-Current and breaks the results in to recession periods and expansion periods. We then move to testing the risk premium using the Ichimoku Cloud in the U.S. from 1988-Current as well as Germany, Canada and the U.K.

We test a variety of these Ichimoku Cloud signals in the first section of the paper on the U.S. stock market. We compare them to the moving average 2,12 and a random generated entry. The moving average 2 denotes 2 periods of arithmetic average and 12 denotes 12 peroids of arithmetic average.

We benchmark success as T stat above 1.68. For economic significance we benchmark R^2 above .5 percent. [2)] We find higher returns with reduced risk for the Ichimoku when compared to the moving average and random entry. We use the wild bootstrap procedure for computing risk premium. (Mooney, Duval 1993).

A. Literature

The Ichimoku Cloud has been shown in literature to provide profitable returns on stock index trading (Deng et al (2021). Lutey and Rayome (2020) show that the Ichimoku Cloud can be useful for short signals on monthly data. Other papers by Gurrib (2020) and Biglieri and Almeia (2018) show that the Ichimoku Cloud can be useful for a trading signal on individual stocks.

Moving averages have been shown to be profitable in literature in articles such as Brock et al (2000), and Neeley et al (2014). Brock et al (2000) also test a trading range breakout strategy.

Most technical indicator studies since 2000 relate to Lo et al (2000) which tests several nonlinear technical chart patterns. The uniqueness of Lo et al (2000)'s work is that it is based on smoothing stock prices and obtaining inflection points to generate a rules based system of automated trading. The paper notes that these indicators are harder to construct than typical asset pricing model tests such as the Capital Asset Pricing Model (CAPM). The author also tests the indicators based on increasing volume as well as stand alone. They find that when conditioning on a completed pattern the market shows abnormal returns. The patterns don't show when simulated by a random walk which is in contrast to the typical theory that stock prices follow a random stochastic process.

Volume has also been widely accepted by academic literature for forecasting stock prices. As noted in Lo et al (2000) the joint distribution between prices and volume is not argued only the joint distribution between prices and past prices. Blume et al (1999)

2) A monthly R^2 above .5 percent can represent an economically significant degree of equity risk premium predictability (Campbell and Thompson 2008).

provide the framework for analyzing volume. They show that it can be used as a useful technical indicator.

Technical analysis has shown a recent surge in the literature especially around moving averages. Han et al (2016) show that a moving average trend factor can generate substantial return forecasting based on lagged values of beta. Han et al (2013) use the moving average to successfully time portfolios sorted by volatility.

Momentum studies have been shown in literature and are often referred to by moving average studies as justification for their acceptance. Chan and Jegadeesh (1996) justify the return predicabiltiy of momentum as market underreaction to information. Han et al (2013) note the success of a moving average strategy to be because market participants don't always act on information when it is available to them. Neeley et al (2014) discuss the effectiveness of technical indicators in the presence of macro fundamentals as their ability to pick up on omitted fundamental variables that don't exist (i.e. political uncertainty). Whichever the explanation used, volume is shown to predate moves in prices.

Recent articles on distress risk show that unsystematic distress risk is predicted by profitability, momentum, and firm-specific volatility. (Yun, Kim 2022). Park et al (2022) show that value stocks exceed growth from 2000-2012 in korea. Both studies can be updated to the U.S. and other foreign markets.

Dormeier (2011) suggests that volume actually leads price. Further noting that when volume reaches extreme levels it can be effective for predicting a price move before it happens.

II. Methodology

We test the predictive value of moving averages in the equity premium framework,

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \epsilon_{i,t+1} \tag{1}$$

Replacing, the $x_{i,t}$ in the first equation, with a dummy variable representing (1 or 0) with the in or out signal on a technical indicator. This equation is the general set up for regressing next month's return on an explanatory indicator and can represent the regression framework for studying the role of a technical indicator.

We keep our timeframes for the Ichimoku cloud consistent with the periods outlined in Linton (2010). We compare the results (R^2, β) with the strategies outlined in Neeley et al (2014).

$$x_{i,t} = \begin{cases} 1 \text{ if } MA_{x,t} \ \&\rangle\ MA_{1,t} \\ 0 \text{ if } MA_{x,t} \langle MA_{1,t} \end{cases} \tag{2}$$

Where

$$MA_{j,t} = 1/j \sum_{i=0}^{j-1} P_{t-i} \text{ for } j = x,\ l; \tag{3}$$

And updating for the Ichimoku Cloud,

$$x_{i,t} = \begin{cases} 1 \text{ if } P_{t-1} \ \&\rangle\ IM_{i,t-1} \\ 0 \text{ if } P_{t-1} \langle IM_{i,t-1} \end{cases} \tag{4}$$

Where

$$IM_{j,t} = 1/2\left[Max(H_{i-26}) - Min(L_{i-26})\right] \tag{5}$$
$$j = x,\ l;\ \forall i = 1, \cdots,\ n$$

Noting that price can be broken down into Open (O), High (H), Low (L) and Close(P) components. H and L correspond to high and low respectively. Over time frames, 52, 26, 9. IM can be broken down in to trading signals following a crossover between long periods l = 9, 26, 52 and short periods x = 1. Noting that the displacement of 26 periods requires 26 bars of trading data to compute the cloud. Linton (2010) outlines the displacement of moving averages, noting that similar procedures can be used to displace and test the traditional technical indicator. The results are compared to the MA periods of s = 2, l = 12.

We also test a random entry dummy, that takes a value of 1 if the random number is above 49 and 0 below. The range of random numbers is from 0 to 100.

$$x_{i,t} = \begin{cases} 1 \text{ if } RE \ \& \geq \ 49 \\ 0 \text{ if } RE \langle 49 \end{cases} \tag{6}$$

$$RE = RandomInteger \tag{7}$$

Returns are calculated by taking the log difference in closing prices, more than the risk-free rate of return.

$$r_{i,t} = \log(x_t / x_{t-1}) - rf_t \tag{8}$$

A. Recession Periods

We identify major recession periods outlined by the Federal reserve bank of St. Louis (FRED). The data encompasses 10 recessions for the full sample. 08/1953-05/1954, 09/1957-04/1958, 05/1960-01/1961, 01/1970-11/1970, 12/1973-03/1975, 02/1980-07/1980, 08/1981-11/1982, 08/1990-03/1991, 04/2001-11/2001, 01/2008-06/2009.

We test the risk premium forecasting of the sample over these time frames by including a USREC dummy in the framework. We also test the expansion periods by including an expansion dummy.

$$r_{t+1} {}^{*} USREC = \alpha_i + \beta_i x_{i,t} + \epsilon_{i,t+1} \tag{9}$$

$$r_{t+1} {}^{*} USEXP = \alpha_i + \beta_i x_{i,t} + \epsilon_{i,t+1} \tag{10}$$

III. Data

We gather data from the S&P 500 dividend adjusted index (SPX) from Bloomberg. We gather data from Amit Goyal (2008) for the risk-free rate from 1927-2014, and assume of constant risk-free rate from 2014-2017.

We break the data in to two samples, one is for 1950-2017, and the other is from 1987-2017. Noting that there is a key difference in the results post 1987, which may be due to regulation following the crash of 1987. We also test for a structural break between pre-and post 1987, finding there is a difference in the returns.

For the foreign market testing we use data for the U.S., Germany, Canada and the U.K. from datastream. We use a sample period of 1988-Current.

B. Decades

We break the data in to decades for the full sample, testing a start date every 10 years, with the end date of 2017. We note that significant findings come post 1987. This may have to do with the structural break in the data.

IV. Section 1. Initial Justification

We test our regression framework over the full sample period, and then we break the sample period into decades, following the assumption that the results may be more significant in later periods. We break the data into the samples following the framework of Julien Chevallier (2009) who notes the effect of macroeconomic variables on carbon futures differ significantly following regulation involving the credit crisis.

The indicators are highly correlated so We use resampling in our p- values via wild bootstrap method. We find that many of the indicators are not significant when exposed to the full sample. When broken into decades post 1986 the moving average indicator from Neely is significant on R squared along with the Ichimoku of similar time frame. The Random Entry is not significant in more than one period. The random entry signifies that the investor gaining exposure in a strong bull market may earn excess returns regardless of the indicator he is choosing.

We test on R^2, noting from literature that R^2>0.5% is significant for this type of study. We also study t-statistics, noting that the Ichimoku is the only indicator to earn a positive t statistic at any point in the sample.

We first plot the equity premium by date to see the results visually:

We test for a structural break around the 1987 period, noting the results appear to support this test. To test this, We use a dummy that equals 0 before the proposed break and 1 after. We include the dummy up to three lags. The regression model looks as follows:

$$Lprice = a + D1Lprice(t-1) + D2Lprice(t-2) + D3Lprice(t-3) + et \quad (11)$$

The results do not reject the F test, under the null hypothesis that there is a structual break.

We enact the variables, so they can earn their respective return for in the market days. For simplicity, and lack of accounting for transaction costs We do not have them earn the RF on out of the market days. These two tables show the indicator coorelations over the full sample as well as the summary statistics

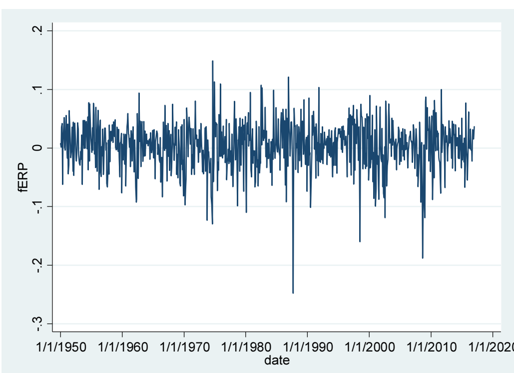

Figure 1. Monthly Equity Risk Premium

for days in to days out of the market. We can see with the random entry (RE) we are in roughly 50% of the time while with the Ichimoku Cloud we are in as much as 87.95% of the time.

Calculations and formulas for the arithmetic mean, geometric mean, standard deviation, and Sharpe ratio are in the Appendix 1.

ERP = Market return. All returns are more than the risk-free rate.

This shows that the means are highest for the market, all the indicator variables miss the highest market return. The Sharpe ratio is highest for the Market. This suggests that the technical indicators do a poor job over our sample period.

We test the data using the risk premium framework previously outlined. We omit results pre-1986 as they are not significant. The table omits results pre-1986 as none of the indicators are significant. We only report significant results. From this point forward we focus on 1986-Present.

The risk premium is shown by the slope coefficient as a percent. The p-value is from the t-statistic. The

Table 2. Summary statistics

Indicator Obs = 730	Mean	Standard Deviation	Min	Max
RE	.5068	.5002	0	1
$MA_{2,12}$	.7055	.4561	0	1
$IM_{1,26,52}$	.7055	.4561	0	1
$IM_{1,9}$	.7781	.4158	0	1
$IM_{1,52}$	.8795	.3258	0	1
$IM_{1,52}$ & $IM_{1_{-26},52_{-26}}$	.8785	.3382	0	1

Table 1. Correlations

Indicator	$MA_{2,12}$	$IM_{1,26,52}$	$IM_{1,9}$	$IM_{1,52}$	$IM_{1,52}$ & $IM_{1_{-26},52_{-26}}$	RE
$MA_{2,12}$	1.0000					
$IM_{1,26,52}$	.2632	1.0000				
$IM_{1,9}$	.7252	0.3911	1.0000			
$IM_{1,52}$	.3965	0.6724	0.5781	1.0000		
$IM_{1,52}$ & $IM_{1_{-26},52_{-26}}$	.4029	0.6866	0.5922	0.9628	1.0000	
RE	-.0346	.0171	.0026	.0309	.0246	1.0000

Table 3. Return enacted summary statistics

Indicator Obs = 805	Arithmetic Means	Geometric Means	Standard Deviation	Min	Max	Sharpe Arithmetic	Sharpe Geometric
RE	.00224	.0201	.0272	-.2479	.1213	.0824	.7390
$MA_{2,12}$	.00224	.0202	.0332	-.2479	.1213	.0675	.6084
$IM_{1,26,52}$	.0017	.0208	.0321	-.2479	.1213	.0530	.6480
$IM_{1,9}$	.0021	.0202	.0357	-.2479	.1213	.0588	.5662
$IM_{1,52}$	.0016	.0202	.0357	-.2479	.1213	.0448	.5662
$IM_{1,52}$ & $IM_{1_{-26},52_{-26}}$	.0014	.0204	.0357	-.2479	.1213	.0392	.5715
ERP	.0036	.0213	.0415	-.2479	.1485	.0867	.5133

Table 4. Post 1986 returns

Indicator	4/1/1986	4/1/1996*	4/1/2006	Sharpe* 0.88
$MA_{2,12}$				
Slope	0.46	0.96	0.26	
P value	0.467	0.226	0.817	
R Sq.	0.2	.93*	0.07	
$IM_{1,9}$				
Slope	0.97	1.67*	1.6	
P value	0.182	0.038*	0.269	
R Sq.	0.76*	2.51*	2.13*	
RE				
Slope	0.05	0.63	0.3	
P value	0.921	0.285	0.677	
R Sq.	0.00	.50*	0.12	

*denotes significant result. Results for slope and R^2 are percents.

R^2 shows that it is above 0.50 which indicates economic significance. Statistically it is seen as a weak relationship[3]. On R^2, the Ichimoku is significant in all three decades after 1986. The Moving average is significant only from 1996-2017. So is the Random Entry. This seemingly nullifies the results, however the Ichimoku earns a statistically positive t statistic in this period which may lead one to believe it is superior to other methods (in this time frame). We explore this later with application on the U.S. and foreign equity markets. We also explore this time frame during recession and expansion periods.

A. Recession

The above tables show us that the indicators are almost all out of the market during the recession period. The Moving Average (MA,2,12) keeps us out of the market more than the other indicators. Ichimoku has us more in the market than the other indicators including the random entry. We enact the returns in Table 6 shows us that all of the indicators earn a negative return. The moving average and Ichimoku 1,9 save some returns while the random entry proves to be the most useful.

No indicator earns a positive t statistic in this time frame. The Ichimoku, and the Moving average are statistically significant on R^2 for all three decades. The Random entry seemingly nullifies the results after 2008, earning a positive R^2 value, although lower than both the moving average, and the Ichimoku cloud. The Ichimoku has the highest R^2 post 2008.

This table shows that although prior literature shows technical indicators to be responsive in forecasting risk premium in the U.S. during recession periods, we cannot find a positive significant result here. The Ichimoku Cloud detects 0.78 percent risk premium during the 2001 recession while the 2008 recession it detects 1.46 percent which is more than the moving average in the later period and less in the earlier period.

B. Expansion

The two tables here show that the indicators are

3) (*Moore, D. S., Notz*, W. I, & Flinger, M. A. (2017) in that an R-squared term below 0.5 is seen as being a weak relationship)

more active during expansion periods. We see the Ichimkou Cloud on from 54%-68.61% of the time while the moving average is on around 61.5% of the time and the random entry is on 46.65%. On means that we are earning market return when the indicator is on.

For Expansion periods, the Ichimoku is significant on R^2 from 1997-2017. The Moving average is Not. The Moving average is significant 2008-2017 while the Ichimoku is not. Neither indicator is significant from 1986-2017. The Random entry is not a factor in expansion periods.

C. Summary of Results

It is interesting that from all the indicators tested, the same three are significant when tested over all time frames, recession time frames, and expansion time frames. It is significant to find that the $IM_{1,9}$ Indicator is significant along with the $MA_{2,12}$ which was highly significant in earlier studies. This shows that the inclusion of the Ichimoku may have similar

Table 7. Recession period equity risk premium

Recession	7/1/1990-3/1/1991	4/1/2001-11/1/2001	1/1/2008-6/1/2009
$MA_{2,12}$			
Slope	0.36	0.823	1.08
P value	.402	.117	.241
R Sq.	0.58*	2.55*	2.77*
$IM_{1,9}$			
Slope	0.50	0.78	1.46
P value	0.326	0.163	0.230
R Sq.	0.96*	2.08*	4.1*
RE			
Slope	0.17	0.30	0.69
P value	0.4240	0.3220	0.1750
R Sq.	0.19	0.43	1.46*

*denotes significant result. Results for slope and R^2 are percents.

Table 5. Summary statistics recession

Indicator Obs = 730	Mean	Standard Deviation	Min	Max
RE	.0658	.2480	0	1
$MA_{2,12}$	.0236	.1519	0	1
$IM_{1,26,52}$	.0980	.2975	0	1
$IM_{1,9}$	.0447	.2067	0	1
$IM_{1,52}$	.1017	.3025	0	1
$IM_{1,52}$ & $IM_{1_{-26},52_{-26}}$	.1005	.3008	0	1

Table 8. Summary statistics expansion

Indicator Obs = 730	Mean	Standard Deviation	Min	Max
RE	.4665	.4868	0	1
$MA_{2,12}$	.6154	.4986	0	1
$IM_{1,26,52}$	.5409	.4740	0	1
$IM_{1,9}$	.6600	.4608	0	1
$IM_{1,52}$	.6948	.4644	0	1
$IM_{1,52}$ & $IM_{1_{-26},52_{-26}}$	.6861	.4992	0	1

Table 6. Returns recession

Indicator Obs = 805	Arithmetic Means	Geometric Means	Standard Deviation	Min	Max	Sharpe Arithmetic	Sharpe Geometric
RE	-.0003	.0348	.0131	-.1296	.1133	-.0229	2.6565
$MA_{2,12}$	-.0007	.0381	.0083	-.1099	.0535	-.0843	4.5904
$IM_{1,26,52}$	-.0014	.0287	.0172	-.1881	.1072	-.0814	1.6686
$IM_{1,9}$	-.0010	.0305	.0108	-.1234	.0626	-.0926	2.8241
$IM_{1,52}$	-.0015	.0287	.0175	-.1881	.0626	-.0857	1.6400
$IM_{1,52}$ & $IM_{1_{-26},52_{-26}}$	-.0015	.0287	.0175	-.1881	.1072	-.0857	1.6400
ERPUS	-.0013	.0291	.0218	-.1881	.1485	-.0596	1.3349

Table 9. Returns expansion

Indicator Obs = 805	Arithmetic Means	Geometric Means	Standard Deviation	Min	Max	Sharpe Arithmetic	Sharpe Geometric
RE	.0034	.0211	.0255	-.0993	.1213	.1333	.8275
$MA_{2,12}$	.0029	.0201	.0293	-.2479	.1213	.0989	.6860
$IM_{1,26,52}$	.0031	.0200	.0282	-.2479	.1213	.1099	.7092
$IM_{1,9}$	.0032	.0199	.0302	-.2479	.1213	.1060	.6589
$IM_{1,52}$	.0031	.0196	.0310	-.2479	.1213	.1000	.6323
$IM_{1,52}$ & $IM_{1_{-26},52_{-26}}$	.0029	.0197	.0310	-.2479	.1213	.0935	.6355
ERPEX	.0050	.0206	.0352	-.2479	.1213	.1420	.5852

Table 10. Expansion period equity risk premium

Expansion	Omit 7/1/1990-3/1/1991	Omit 4/1/2001-11/1/2001	Omit 1/1/2008-6/1/2009
$MA_{2,12}$			
Slope	0.10	0.142	-0.82
P value	0.841	0.801	0.171
R Sq.	0.01	0.03	1.30*
$IM_{1,9}$			
Slope	0.47	0.89	0.14
P value	.365	.130	.825
R Sq.	0.23	9.8*	0.03

*denotes significant result. Results for slope and R^2 are percents.

value to moving averages when studying in an equity premium framework.

D. Lagged Values

We test lagged values of the indicators over the full sample to see if traders may delay their entry when getting a in or out signal.

We find no significant results for first through fifth lags of the moving average, however strong significant results for the first lag of the Ichimoku OT variable.

This shows some sign that the Ichimoku may contain added value over the moving average when lagged. Which is an appropriate use of the cloud when noted by traders.

Table 11. Lagged returns

4/1/1956 Lags 1-5	Slope	P value
$MA_{2,12}$	N/A	N/A
$IM_{1,9}$	1.24	.045*

*denotes significant result. Results for slope and R^2 are percents.

We explore this further in the next section while testing the risk premium in the U.S. as well as Germany, Canada and the U.K.

V. Summary

We find initial justification for using the Ichimoku Cloud in the U.S. risk premium forecasting in the main body of the paper. Results are mainly inconsistent and inconclusive. However, this seems to be a fitting theme with equity premium papers. Some authors (Goyal (2008)) find that macroeconomic variables do not contain added value, while Neeley et al (2014) find they do, and find that technical indicators contain value more than macro variables. It appears the cloud may contain added value, and strong significance when taking the first lag.

VI. Section 2. Empirical Results

We extend the predictive regression above where next months return is regressed on this month's predictive indicator. In this case it is the Ichimoku for 9 periods, 26 periods, 52 periods and a crossover between 9 and 26.

$$Ichimoku \equiv IM_i = \frac{1}{2}(Max[\ High(i)] - Min[\ Low(i)]); \quad i = 9,26,52 \tag{12}$$

$$x_{i,t} = \begin{cases} 1 \text{ if } P_{t-1} \ \ \&\rangle\ IM_{i,t-1} \\ 0 \text{ if } P_{t-1}\langle IM_{i,t-1} \end{cases} \tag{13}$$

The Ichimoku Cloud is noted as our predictive variable for forecasting next months stock return. The Cloud is given an entry point between the previous price and the previous estimate for the Ichimoku Cloud. Without look ahead bias. For the current period 1,9 the price at the previous period (t-1) is used and the Ichimoku Cloud (9) is used at period (t-1). Periods 26 and 52 follow similar.

For 9,26 we use the following equation:

$$x_{i,t} = \begin{cases} 1 \text{ if } IM_{9,t-1} \ \ \&\rangle\ IM_{26,t-1} \\ 0 \text{ if } IM_{9,t-1}\langle IM_{26,t-1} \end{cases} \tag{14}$$

This entry notes that we enter when last months Ichimoku 9 is above last months Ichimoku 26. Without look ahead bias. We exit in the current period when the last months Ichimoku 9 is below the last months Ichimoku 26.

We carry this out in the U.S., U.K., Canada, and Germany. We obtain data from Factset for 1988-2021. We show results in the following section.

We avoid look ahead bias by completing an indicator prior to the current period. That is, we enter in the next period following a complete indicator. We run our regression for the following period.

A. Results

This shows that the Ichimoku Cloud is effective in forecasting risk premium in the U.S. and each of the U.K., Germany, Canada, and Spanish Stock Markets. Ichimoku 1,52 isn't successful in Canada but is successful everywhere else. The 1,9 signal is the strongest signal in most markets along with the 9,26 crossover.

Table 12. U.S. stock market 1988-2021 - Ichimoku cloud

Ichimoku	Slope	T Stat	R^2
1,9	3.42*	6.08	10.69*
1,26	2.21*	3.71	4.27*
1,52	1.28*	2.02	1.30*
9,26	3.35*	5.66	9.38*

*denotes significant result. Results for slope and R2 are percents.

Table 13. German stock market - DAX 1988-2021

Ichimoku	Slope	T Stat	R^2
1,9	1.68*	3.67	3.31*
1,26	1.38*	2.88	2.06*
1,52	1.23*	1.33	2.30*
9,26	1.94*	4.01	3.92*

*denotes significant result. Results for slope and R2 are percents.

Table 14. Canada stock market - CAC 1988-2021

Ichimoku	Slope	T Stat	R^2
1,9	1.66*	3.71	3.78*
1,26	0.99*	2.24	1.25*
1,52	0.52	1.14	0.33
9,26	1.37*	3.09	2.36*

*denotes significant result. Results for slope and R2 are percents.

Table 15. U.K. stock market - FTSE -100 1988-2021

Ichimoku	Slope	T Stat	R^2
1,9	2.73*	6.24	9.00*
1,26	1.91*	3.84	3.61*
1,52	1.05*	1.91	0.92*
9,26	2.17*	4.49	4.87*

*denotes significant result. Results for slope and R2 are percents.

VII. Limitations

The study uses already known indicators for predicting stock returns from print literature. It would benefit from real time analysis and true out of sample robustness testing which would be left up for future work. I.e. fund managers implementing the methodology and recording it in a trading journal or trading account.

VIII. Conclusion

We run predictive regressions in the U.S., Spain, U.K., Germany and Canada. We show that the Ichimoku Cloud is predictive in this format. We note high return predictability and high statistical significance and robustness of each indicator across our sample.

We show that the 1,9 period (Price crossing above the 9 period Ichimoku Cloud 'tenkansen' or 'turning line') is highly predictive consistently across each country we test. We show that the 9,26 (tenkensen-kijunsen, or turning line standard line) crossover is also predictive consistently. The 1,52 period (Price crossing 'Span B') is the weaker signal although still statistically significant in most countries. This suggests the indicators can be useful in the U.S. and foreign stock markets.

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