Excess Returns Unleashed: Dynamic Momentum-Contrarian Strategy with Ichimoku

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Abstract: - Previous studies of momentum strategies and contrarian strategies have focused on debating the advantages of each strategy separately without attempting integration. The aim of this study was to test the effects of combining these two strategies into a dynamic approach, using Ichimoku as a mediator. This quantitative research uses daily stock prices taken from the Indonesia Stock Exchange website to analyze the mechanism of the relationship between heuristics and investment performance. Our research demonstrates the superior performance of the Dynamic strategy in generating higher returns when compared to alternative strategies. One of the main reasons behind this success is how well Ichimoku can navigate this indirect influence. The proposed model demonstrates strong predictive abilities and sets itself apart from the strategies that influence its development. Investors of all backgrounds, including individuals, can easily integrate this innovative strategy. Therefore, the study makes a valuable contribution to improving investment strategies, making them more comprehensive and effective.

Key-Words: - 52 Week High-Low, Anchoring; Contrarian, Strategy, Dynamic Strategy, Ichimoku, Momentum Strategy, Representativeness.

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1 Introduction

Investment judgments often rely on anchor and representative heuristics, particularly when technical analysis lacks robust information support. These heuristics assist in simplifying intricate situations and rapidly assessing the likelihood of events under time limitations, [1]. The anchor and adjustment heuristics involve using initial reference values and modifying them based on further information [2], [3], [4]. These heuristics help simplify complex situations and quickly assess event probabilities when time is limited. The anchor and adjustment heuristics involve making adjustments to initial reference values based on new information. In contrast, "representativeness heuristics" involves assessing how closely an event matches a particular category. Investors often anticipate success with high-performing stocks and frequently rely on representativeness heuristics to develop trading strategies, [5]. Understanding heuristics in investment decision-making is crucial for both investors and policymakers because it elucidates how individuals navigate uncertainty in financial markets.

One commonly used rule of thumb in investment decision-making is to consider the highest (lowest) price within the last 52 weeks, [6]. This data is easy to find through various commonly used trading platforms, such as TradingView.com, Investing.com, and even the official website of the Indonesia Stock Exchange.

Using heuristics in investment decision-making may deviate from the efficient market hypothesis; therefore, investors must understand how to employ them [7], [8]. For instance, when contemplating the use of the representativeness heuristic, several traders rely on the presumption that equities priced at a 52-week high (or low) are either overvalued or undervalued. This impression frequently leads traders to fail to respond to the available information. However, as this information proves accurate over time, traders will adjust their methods. This adjustment encourages a sustainable trend-direction pattern, [9].

The use of heuristics creates bias. Some previous researchers have obtained evidence regarding the reliability of momentum strategies, namely strategies that buy shares that perform well and sell shares that perform poorly, in generating excess returns, [10], [11], [12], [13], [14]. Conversely, some traders view stocks that are near 52-week highs (lows) as indicators of stocks with over- (or under-) performance. This view, however, often results in an overreaction. When this perception proves misguided, traders readjust their opinions, which contributes to long-term price reversals, [15], [16]. Empirical evidence also suggests that contrarian strategies, such as buying underperforming stocks and selling well-performing stocks, can offer superior returns, [17], [18], [19], [20], [21], [22]. This observation highlights a significant gap in the field's knowledge and underscores the importance of understanding how traders employ heuristics to craft more precise investment strategies when making investment decisions. To maximize returns for investors, such schemes must carefully consider behavioral biases and market dynamics.

This observation highlights a gap in current research, emphasizing the importance of understanding how traders use heuristics to develop more appropriate and effective investment strategies. To maximize investor returns, it is important for strategies to take behavioral biases and market dynamics seriously.

Additionally, previous research often advocates one approach over another without considering that integration is often the best approach. However, these obstacles have hampered our ability to study how market dynamics interact with investment outcomes. One distinct limitation is that, with a few exceptions distinct limitation is that, with a few exceptions, [23]. The literature does not offer detailed causal mechanisms to explain how heuristics can impact investment performance. Ignoring these gaps will prevent us from fully understanding how they affect our bottom line (costs).

The aim of this study is to bridge that gap process-wise by dissecting momentum and contrarian strategies in a dynamically integrated manner, with Ichimoku as the mediator. Despite its prognostic capabilities, Ichimoku remains relatively unexplored. By adopting an integrative methodology, this research paper presents a new viewpoint that highlights the benefits of dynamic strategies compared to other evaluated approaches. This research aims to explain the complex interrelationships among various investment strategies and evaluate the predictive validity of the model we have developed. Furthermore, our research seeks to establish significant distinctions between dynamic strategies and other methodologies that have undergone testing.

This study's novelty lies in its attempt to fill a gap in understanding the basic mechanisms linking heuristics to investment performance. We underscore the potential of this research to bridge existing gaps in the literature and enhance our comprehension of the intricacies of financial markets and investment dynamics, encompassing phenomena like disposition effects. This study provides a new perspective on investment strategies and improves investors' ability to make informed decisions, thereby potentially improving overall investment performance.

The following sections of the study will explore the proposed model outlined in Part 2, outline the data and methodology described in Part 3, present the results obtained in Part 4, discuss the findings in Part 5, and finally conclude with comprehensive conclusions in the last section.

2 Propose Model

To answer the research question, we propose a model as depicted in Figure 1. This model visually illustrates the direct and indirect influence of Momentum and Contrarian strategies on Dynamic strategies, mediated by Ichimoku. Based on initial predictions, the overall Dynamic strategy shows statistically significant differences compared to the Momentum, Contrarian, and Ichimoku strategies.

The H1 to H7 hypotheses detail the expected influence of various strategies on Dynamic strategies. These influences include both direct and indirect impacts. Direct impact refers to the direct influence of each strategy on the Dynamic strategy. Hypotheses 1, 2, and 3 propose the positive impact of Momentum, Contrarian, and Ichimoku strategies on Dynamic Strategies, while Hypotheses 4 and 5 note the positive impact of Momentum and Contrarian strategies on Ichimoku strategies.

In addition, we also pay attention to the indirect influence of each strategy on Dynamic strategies through Ichimoku. Hypotheses 6 and 7 hypothesize that Momentum and Contrarian strategies influence Dynamic strategies after mediation by Ichimoku.

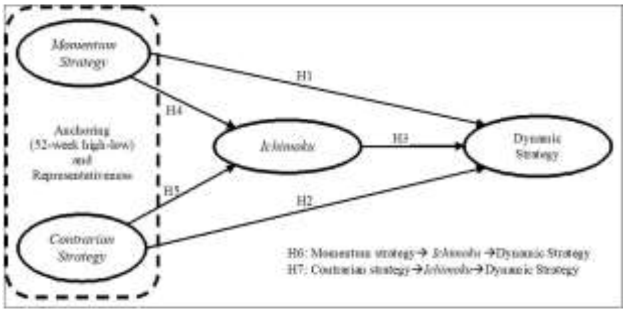

Fig. 1: Encapsulates the research model, outlining the hypothesized relationships among Momentum, Contrarian, Ichimoku, and the resulting Dynamic strategy.

3 Data and Methodology

3.1 Samples and Procedures

This research uses a quantitative approach to analyzing stock price movements in the Indonesian market. The secondary data used is the daily stock price taken from the Indonesia Stock Exchange website, which is [24]. This data set was strategically selected to cover the time span from January 3, 2017, to September 29, 2023, so as to capture various market conditions, including when the market is in a bullish and bearish trend. A comprehensive accounting of 88 actively traded equities has been recognized. We have compiled complete data on these equities, taking into account dividends and stock splits. The return calculation will begin on January 2, 2018. This comprehensive data set provides a solid foundation for careful study and in-depth observation of various market conditions.

3.2 Winner and Loser

We used a two-step heuristic process rooted in holds to distinguish the good picks from the bad ones in our stock-picking methodology. Here, the method rests on two key points of reference: price highs and lows that occurred in the past 52 weeks [6]. We calculate the winners and losers through the Nearest Ratio (NR), a comparison of the close price with the 52-week low within the range of its highest and lowest prices in the same period. This formula for the closeness ratio is one of the key parts of our data analysis.

Winning stocks are those stocks that are nearest their all-time high and losing stocks are those closest to their all-time low in finance. Using the Nearest Ratio (NR) that compares the closing price to the 52 weeks, we classify winners and losers:

$$NR = \frac{P_{i,t-1} - Low_{i,t-1}}{High_{i,t-1} - Low_{i,t-1}} \quad (1)$$

Where NR is nearest ratio in this equation the 52 weeks high or low where $P_{i,t-1}$ is the previous day's closing price. Beside that $High_{i,t-1}$ and $Low_{i,t-1}$ mean the 52-week high/low prices of the stock the fortnight ending yesterday, t−1. The calculation of NR will result in a value that ranges from 0 to 1. A higher value indicates that the price has approached the highest price in the last 52 weeks and vice versa.

The determination of Winner and Loser shares is based on the magnitude of NR value with a threshold of 30% [6], [25]. The selection of these thresholds is to ensure a degree of precision, empirical support, consistency with heuristic practices, noise reduction, and wide applicability across a wide range of market conditions. This method can increase the durability and practicality of the chosen trading strategy. Winners are identified as stocks with an NR value exceeding 70%, while losers are stocks with an NR value of less than 30%.

3.3 Ichimoku

The method was started in the late 1930s and expanded even more in the 1960s. When translated from Japanese, the term "Ichimoku Kinko Hyo" means "one glance equilibrium chart", [26]. Ichimoku reflects in its very name what it does best: it offers a "glance" at a chart and directly shows the equalized price movement in its entirety.

Ichimoku, a multifaceted and user-friendly analytical tool, may be utilized across many investing time frames and asset categories. Traders and analysts find Ichimoku to be an indispensable resource due to its remarkable adaptability in identifying trends, evaluating market momentum, and determining support and resistance levels. Ichimoku is a trading tool utilized by traders to evaluate market momentum, identify trends, and ascertain potential support and resistance levels. "The historical development of the Ichimoku Kinko Hyo concept, from its origins to its modern-day applications, underscores its enduring significance in technical analysis. This underscores the reliability, flexibility, and value of Ichimoku in guiding traders through ever-changing market conditions, underscoring its importance in adapting to shifting trends. By applying the Ichimoku indicator, traders can develop a deeper understanding of market dynamics. This allows them to make decisions based on a thorough analysis of trends and support/resistance levels. Better understanding and intelligent decision-making abilities have the potential to lead to greater profits and success in the financial markets.

The mathematical expressions utilized to compute Ichimoku elements bear conceptual resemblances to conventional moving averages. The method employs a mid-point moving average. The Tenkan-sen (TK) represents short-term moving averages, whereas the Kijun-sen (KJ) represents medium-term moving averages. Senkou-span A (SKA) and Senkou-span B (SKB) might be likened to long-term moving averages. The uniqueness lies in the use of the median of the highest and lowest prices over a certain period in Ichimoku. Chikou-span (CK) serves as a momentum indicator, providing insights into possible trends.

The standard period parameters in Ichimoku are 9, 26, and 52. This systematic approach contributes to Ichimoku's efficacy as a technical analysis tool that is robust and adaptable, [27], [28].

$TK = \frac{Max(Ph_T) + Min(Pl_T)}{2}$	t-8<T<t	(2)
$KJ = \frac{Max(Ph_T) + Min(Pl_T)}{2}$	t-25<T<t	(3)
$SKA = \frac{TK+KJ}{2}$	shifted forward 26 periods	(4)
$SKB = \frac{Max(Ph_T) + Min(Pl_T)}{2}$	t-1<T<t-52 shifted forward 26 periods	(5)
$CK_{t-25} = Pc_{t-0}$	shifted backward 26 periods	(6)

In representing the formulation, where $Max(Ph_T)$ and $Min(Pl_T)$ represent the highest and lowest prices during the T period, and Pc_t denotes the closing prices, the Ichimoku strategy is constructed. The crossover between Tenkan and Kijun is a pivotal indicator of the trend direction. A Tenkan-sen crossover from the bottom to the top of the Kijun-sen signals the emergence of a bullish trend, whereas a crossover from the top to the bottom indicates a bearish trend.

The price position relative to the Kumo, or cloud, provides insights into the trend's strength. In a bullish trend, a bottom-to-top breakout (penetration) of the cloud signifies a robust trend. Conversely, in a bearish trend, a top-to-bottom penetration of the cloud indicates a strong bearish trend. The Chikou-span is employed to confirm trend formation.

3.4 Trading Strategy

Guided by the NR formula, the Momentum strategy ($MOM_{i,t}$) involves purchasing shares with an NR value exceeding 70% and selling shares with an NR value falling below 30%, thus aligning with the established criteria for winners and losers.

$$MOM_{i,t} = \begin{cases} 1\ if(NR > 70\%) \\ 0\ if(NR < 30\%) \end{cases} \tag{7}$$

On the contrary, the contrarian strategy ($CON_{i,t}$) entails purchasing shares with an NR value of less than 30% and selling shares with an NR value exceeding 70%. Concurrently, shares with an NR value falling within 30% to 70% adhere to the established trading signals from preceding periods.

$$CON_{i,t} = \begin{cases} 1\ if(NR < 30\%) \\ 0\ if(NR > 70\%) \end{cases} \tag{8}$$

The Ichimoku strategy amalgamates these five elements to generate buy or sell signals. Three key Ichimoku ($ICH_{i,t}$) rules, encompassing the crossover between Tenkan and Kijun, Tenkan-sen crossover, price position against Kumo, and confirmation by Chikou-span, are integrated to formulate these signals.

$$ICH_{i,t} = \begin{cases} 1\ if\left(and\left(\begin{matrix} Pc_{t-1} > TK, TK > KJ, \\ P_{t-1} > Max(SKA, SKB), \\ CK > Pc_{t-26} \end{matrix}\right)\right) \\ 0\ \ if\left(and\left(\begin{matrix} Pc_{t-1} < TK, TK < KJ, \\ P_{t-1} < Min(SKA, SKB), \\ CK < Pc_{t-26} \end{matrix}\right)\right) \end{cases} \tag{9}$$

A dynamic strategy ($DYN_{i,t}$) is a hybrid strategy that combines momentum and contrarian strategies. This strategy is applied dynamically based on signals generated by the $ICH_{i,t}$. Traders can adopt momentum and contrarian strategies dynamically according to the signals provided by the $ICH_{i,t}$. If no match is found, traders can choose to maintain or liquidate their positions.

$$DYN_{i,t} = \begin{cases} 1\ if(and(or(NR > 70\%, NR < 30\%), \\ \qquad ICH_{i,t} = 1) \\ 0\ if(and(or(NR > 70\%, NR < 30\%), \\ \qquad ICH_{i,t} = 0\ ) \end{cases} \tag{10}$$

Where if the calculation of each strategy yields the number 1, it signifies a buy signal, whereas 0 represents a sell signal.

3.5 Return

Returns of daily stock (R_t) were calculated in percentage using the continuous formula compounded, [29], as follows:

$$R_t = \frac{P_t}{p_{t-1}} - 1 \tag{11}$$

Where the closing prices in periods t and t-1 are set as $P_t$and P_{t-1}. Meanwhile, the benchmark (R_b), a buy and hold strategy, was calculated based on a percentage with the following formula:

$$R_b = \frac{P_t}{p_{t-0}} - 1 \tag{12}$$

Where P_t is the closing price at the end of the research period and p_{t-0} is the closing price at the beginning of the research period. Accordingly, there is the excess return (R_x) , i.e. the difference between the return of each strategy and the return

$$R_x = R_t - R_b \tag{13}$$

3.6 Methodologies

This study presents a new dynamic trading strategy that integrates momentum and contrarian strategies using Ichimoku as a mediator. For this reason, we tested whether there are differences between these trading strategies. Additionally, we analyzed the effects of momentum and contrarian trading strategies on dynamic strategies, considering both direct and indirect impacts. Direct impact relates to the direct influence of each strategy on the dynamic strategy, while indirect impact includes the influence of each strategy on the dynamic strategy through Ichimoku.

3.7 Confirmatory Composite Analysis (CCA)

Confirmatory composite analysis (CCA) was used to assess the quality of measurement models in PLS-SEM, [30], [31]. This approach, an alternative to confirmation factor analysis (CFA), is used to confirm measurement models when using partial least squares structural equation (PLS-SEM) modeling. The evaluation process encompasses three primary steps; however, since the study exclusively employs formative measurements, the evaluation comprises: (1) scrutinizing the formative measurement model by analyzing redundancy, variance inflation factor (VIF), and the significance and relevance of indicator weights. (2) Assessing the structural model through VIF examination, alongside scrutinizing the significance and relevance of path coefficients, explanatory and predictive power, and evaluating the goodness of fit through relevant measures. Given the non-linear dynamics inherent in stock price movements, WarpPLS 8 utilizes a sophisticated non-linear algorithm to navigate these complexities. Given the non-linear nature of stock price movements, WarpPLS 8 uses a non-linear algorithm.

3.8 Kruskal-Wallis test

The Kruskal-Wallis test, a non-parametric analysis tool, was pivotal in evaluating differences among the integrated trading strategies. This method proved well-suited for assessing excess returns, particularly in financial contexts where normality and equal variance assumptions may not hold. By focusing on medians, it provided insights into performance variations across Momentum, Contrarian, Ichimoku, and Dynamic strategies. Subsequently, a post hoc analysis using Dunn's Test delved deeper into the nuances of the results, identifying specific pairs of strategies exhibiting statistically significant differences. This robust statistical approach, with a predetermined threshold of 0.05, enhanced the credibility of our findings, contributing to a nuanced understanding of comparative effectiveness. Additionally, a separate test using SPSS 25 software ensured the distinctiveness of the dynamic strategy from momentum and contrarian strategies.

4 Results

4.1 Descriptive Statistics

The data analysis in Table 1 reveals distinct characteristics for each strategy. The Momentum Strategy (MOM) demonstrates a growth trend, with a positive mean of 0.259, indicating potential for positive returns. Conversely, the Contrarian Strategy (CON) embodies a contrarian trend, with an opposing average of -0.265, suggesting potential losses. Notably, the Ichimoku Strategy (ICH) stands out with a relatively high average of 1,653, showcasing robust performance. However, the Dynamic Strategy (DYN) is the most noteworthy, boasting the highest average of 2,733, denoting substantial profit potential. With a remarkable maximum value of 10,717, the Dynamic Strategy emerges as the superior choice during this research period, albeit with heightened volatility compared to other strategies. Consequently, the data substantiate the conclusion that the Dynamic Strategy exhibits superior yield potential compared to Momentum, Contrarian, and Ichimoku in this observational period.

The histograms in Figure A1 (Appendix) provide a visual representation of how excess returns are distributed across various investment strategies. In the Momentum Strategy, the majority of returns lie between -100% and 300%, with a positive skewness (0.890), suggesting a tendency towards higher positive returns. Conversely, the Contrarian Strategy shows returns primarily within the range of -300% to 100%, exhibiting a negative skewness (-1.628), indicating a prevalence of lower negative returns. For the Ichimoku Strategy, returns are clustered between 0% and 600%, with a positive skewness (1.366), indicating a preference for higher positive returns. Meanwhile, the Dynamic Strategy displays a wider range of returns, centered around 200% to 800%, and the highest positive skewness (1.647), highlighting a strong inclination towards higher positive returns. These insights enable investors to assess the risk and return characteristics of each strategy, with the Dynamic Strategy particularly noteworthy for its potential for higher returns despite increased volatility.

Table 1. Descriptive statistic for indicator

	MOM	CON	ICH	DYN
No. Diff. Vals	88,000	88,000	88,000	88,000
No. diff Vals/N	1,000	1,000	1,000	1,000
Mean	0.259	-0.265	1,653	2,733
SD	0.627	0.708	1,307	2,208
Min	-1,541	-3,593	-0.273	0.040
Max	2,869	1,235	7,002	10,717
Median	0.183	-0.068	1,246	2,078
Mode	-1,541	-3,593	-0.273	0.040
Skewness	0.875	-1,600	1,342	1,619
Exc. kurtosis	3,813	4,821	2,007	2,406

4.2 Evaluation Criteria (Formative Models)

Convergent validity, collinearity, and the importance and applicability of indicator weights were the three main areas of emphasis for this in-depth analysis of the formative models. The study employed redundancy analysis to evaluate convergent validity. The analysis found loading factors with values of 1 and P-values less than 0.001, indicating that the convergent validity was satisfactory, [32]. The collinearity test carried out using the Variance Inflation Factor (VIF) produced values ranging from 1.090 to 1.284. These results indicate that there are no vertical multicollinearity problems in the data. In addition, this study confirmed the significance and relevance of the indicator weights, as all P values were below 0.05. The results of our analysis confirm the dependability and strength of the formative constructs used in our study.

4.3 Evaluation of Structural Models

Evaluation of structural models encompasses several key aspects: Collinearity, Significance, and relevance of path coefficients, Explanatory power, and Predictive power, [30], [31].

4.3.1 Collinearity

In the process of evaluating the structural model, the first crucial step is to assess multicollinearity to ensure the reliability of regression results. This is typically achieved through a comprehensive VIF multicollinearity test. Based on the VIF values reported in Table 2, the variables MOM and CON have relatively low VIF values of 1.184 and 1.099, respectively, indicating minimal multicollinearity. However, the ICH and DYN variables have higher VIF values of 4.758 and 4.512 respectively, indicating potential multicollinearity between variables, but they are still acceptable because they are below the threshold of 5, [30].

Taking care of multicollinearity worries now is crucial. It helps make sure our analyses down the line are solid and precise. When we're sure multicollinearity isn't an issue, we can trust our interpretations of the path coefficients more confidently. Plus, it means we're doing a better job of evaluating how well our model explains and predicts things, which is what we're aiming for [30].

It is crucial to acknowledge and resolve concerns pertaining to multicollinearity during this phase, as doing so enhances the reliability and precision of subsequent analyses. By verifying the lack of substantial multicollinearity, we can proceed with increased certainty in interpreting the importance and relevance of path coefficients. Furthermore, this practice guarantees a more comprehensive evaluation of the explanatory and predictive strength of the structural model, which is consistent with our research aims.

Table 2. Latent Variable Coefficient

	MOM	CON	ICH	DYN
Full collin. VIF	1.184	1.099	4.758	4.512
R-square			0.250	0.705
Q-square			0.253	0.786

4.3.2 Path Coefficient Analysis

Table 3 details the significant findings from the path coefficient analysis regarding the interrelationships among different trading strategies. The first results show that the negative path coefficients for MOM DYN and CON DYN are not statistically significant (-0.084 and -0.068, respectively), as shown by the p-values that are higher than the 0.05 significance level. There is no substantial direct correlation between the momentum strategy (MOM) or contrarian strategy (CON) and the dynamic strategy (DYN). The inference is that the use of MOM or CON does not have a direct impact on the dynamic strategy's efficacy, as previously postulated.

On the other hand, a highly significant positive path coefficient for ICH → DYN (0.821) indicates a strong and positive relationship between the Ichimoku variable (ICH) and dynamic strategy (DYN). Additionally, a significant positive path coefficient for MOM → ICH (0.407) and a significant negative path coefficient for CON → ICH (-0.196) indicate that MOM and CON significantly influence the use of Ichimoku in the context of stock trading.

Table 3. Direct effects and indirect effects of independent variables on dependent and effect size

Hypothesis	Path coefficient (β)	P-value	F - square	Reports
Direct Effect				
MOM →DYN	-0.084	0.212	-0.038	Not supported
CON →DYN	-0.068	0.258	0.023	Not supported
ICH →DYN	0.821 ***	<0.001	0.720	Supported
MOM →ICH	0.407 ***	<0.001	0.189	Supported
CON →ICH	-0.196 *	0.028	0.061	Supported
In direct Effects				
MOM →ICH →DYN	0.271***	<0.001	0.114	Supported
CON →ICH →DYN	0.457***	<0.001	0.079	Supported

Note: MOM=Momentum Strategy, CON=Contrarian Strategy, ICH=Ichimoku, DYN=Dynamic Strategy
N= 88.
** Significant at 0.05.*
*** Significant at 0.01.*
**** Significant at <0.01.*

In addition, the findings indicated that the indirect impacts of MOM and CON on DYN through ICH (0.271 and 0.457, respectively) were also statistically significant. These results provide support for the hypothesis that Ichimoku facilitates the integration of MOM and CON, thereby significantly augmenting the performance of dynamic strategies.

This underscores Ichimoku's mediating role in the relationship between MOM/CON and DYN. Although some hypotheses were not supported, the results of this study show that Ichimoku has a significant influence as a mediator between momentum, contrarian, and dynamic strategies in the trading context.

4.3.3 Explanatory Power

Next, the Explanatory Power test was conducted using the R-square value to assess the extent to which independent variables can explain the variation in the dependent variable. In the context of this study, an R-square value of 0.250 for ICH indicates that MOM and CON still have relatively low explanatory power. It is important to note that R-square values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak predictors, respectively [30]. The contributions of MOM and CON to the R-square value, at 0.189 and 0.061 for MOM → ICH and CON → ICH respectively, suggest a moderate and weak contribution of both variables to the variation in ICH. As a guide, f-square values of 0.02, 0.15, and 0.35 respectively represent small, medium, and large effects of an exogenous latent variable, [32].

However, collectively they offer a moderately explanatory power for DYN, as indicated by an R-square value of 0.705. Furthermore, the fact that the R-square value remains below 0.90 indicates that the model does not suffer from overfitting [30]. The contributions of MOM, CON, and ICH to the R-square value of DYN (-0.038, 0.023, and 0.720 respectively) suggest a moderate impact for MOM and CON, and a substantial impact for ICH. It is noteworthy that MOM's contribution is opposite to the direction of DYN. These findings suggest that MOM and CON have a greater impact when mediated by ICH compared to when they directly influence DYN.

4.3.4 Predictive Power

The Q-square value provides insight into a model's overall predictive performance by demonstrating its ability to forecast outcomes that are not included in its training set. The diagram shows that this model has Q-square values of 0.253 for ICH and 0.786 for DYN, indicating a fair predictive ability for information not explicitly provided. Higher values indicate superior accuracy, whereas increasing values indicate improved predictive ability of the model. The Q-square value is greater than 0.00, 0.25, and 0.50, as stated by [30], showing varying levels of prediction accuracy in PLS path models. A Q-square value between 0.00 and 0.25 indicates a satisfactory level of prediction accuracy. A Q-square value greater than 0.50 indicates a high level of prediction accuracy. Due to the fact that it can predict outcomes for DYN with a high degree of accuracy and moderate accuracy for ICH, the model is consequently capable of predicting results that extend beyond its trained data.

4.4 Goodness of Fit

After thoroughly evaluating the model fit and quality indices, Table 3 demonstrates that the proposed model Fit and Quality Indices, Table 4 displays that the proposed model fits the original data better than other models.

Table 4. Model fit and quality indices

Items	Value	Rule of thumb	Note
Average path coefficient (APC)	0.315	P<0.001	significant
Average R-squared (ARS)	0.478	P<0.001	significant
Average adjusted R-squared (AARS)	0.464	P<0.001	significant
Average block VIF (AVIF)	1.172	acceptable if <= 5, ideally <= 3.3	ideal
Average full collinearity VIF (AFVIF)	2.888	acceptable if <= 5, ideally <= 3.3	ideal
Tenenhaus GoF (GoF)	0.691	small>=0.1, medium>=0.25, large>=0.36	large
Simpson's paradox ratio (SPR)	0.800	acceptable if >= 0.7, ideally = 1	acceptable
R-squared contribution ratio (RSCR)	0.963	acceptable if >= 0.9, ideally = 1	acceptable
Statistical suppression ratio (SSR)	1.000	acceptable if >= 0.7	acceptable
Nonlinear bivariate causality direction ratio (NLBCDR)	1.000	acceptable if >= 0.7	acceptable

4.5 Normality Test

Table 5 displays significant deviations from the normal distribution across all techniques, as evidenced by the Kolmogorov-Smirnov test. This divergence highlights the non-normally distributed nature of the data, indicating that non-parametric tests, like the Kruskal-Wallis test, might be a more appropriate option for study, [33].

Table 5. Normality Test

Strategy		Kolmogorov-Smirnova		
		Statistic	df	Sig.
Excess Return	Strategi Momentum	0.133	88	0.001
	Strategi contrarian	0.131	88	0.001
	Ichimoku	0.191	88	0.000
	Dynamic Strategy	0.177	88	0.000

a Lilliefors Significance Correction

4.6 The Kruskal-Wallis test

The Kruskal-Wallis test was conducted to evaluate the differences in rankings among various strategies based on Excess Return. Results in Table 6 indicate significant findings (H=223.704) with 3 degrees of freedom and a p-value of 0.000, signifying significant rank variations among the strategies. This variation suggests statistically significant differences in Excess Return across all strategies. Mean ranks were used to determine performance order, with the Dynamic Strategy having the highest average rank (273.36), followed by Ichimoku (235.85), Momentum (123.05), and Contrarian (73.74). These results indicate that the Dynamic Strategy tends to outperform the others, while the Contrarian Strategy shows relatively lower performance. The Kruskal-Wallis test provides strong evidence that the integration of momentum and Contrarian strategies, mediated by Ichimoku, yields a new strategy distinct from its constituent strategies.

Table 6. Kruskal Wallis Test.

Variables	N	Mean Rank	Kruskal-Wallis	Sig.
Excess Return				
Momentum Strategy	88	123.05	223.70	0.000
Contrarian Strategy	88	73.74		
Ichimoku	88	235.85		
Dynamic Strategy	88	273.36		
Null Hypothesis			Test	
The distribution of Excess Return is the same across strategy categories.			Independent-sample Kruskal Wallis	0.000

Asymptotic significances are displayed. The significance level is .05

Following the rejection of the null hypothesis in the Kruskal-Wallis test, Dunn's test is employed for post-hoc analysis to explore specific pairwise comparisons among the strategies. While Dunn's test does not provide individual p-values for each pair, a significant p-value (less than 0.05) indicates a statistically significant difference in excess return between those strategies.

5 Discussion

When evaluating the Momentum and Contrarian strategies, Momentum achieves a higher excess return compared to the Contrarian Strategy. Investing in stocks based on their proximity and recent performance relative to 52-week highs significantly increases the likelihood of a positive outcome, [34] These findings are in line with research showing that gains gained from 52-week highs include momentum gains [6], thus challenging the notion of semi-strong form efficiency, [35].

Turning to Ichimoku, the Ichimoku Strategy reveals its capacity to generate positive excess returns that surpass the Momentum Strategy. This methodology, which covers a wider range of bullish and bearish signals, provides more accurate insights into market trends and price conditions, [36]. Prior studies have additionally confirmed the capacity of Ichimoku to identify the commencement and deduction of trends, [37], [38]. Similar to the moving average method, Ichimoku is effective in filtering out market noise and accurately identifying trends. Its breakout methodology allows the initial identification and precise conclusion of trends in line with established technical trading principles, [39], [40] The evidence substantiating the superiority of the Ichimoku Strategy over the Momentum Strategy proves the dependability and uniformity of Ichimoku's effectiveness in identifying trends. These results underscore the critical role of Ichimoku in influencing market dynamics and underscore its efficacy in facilitating trading strategies.

The most appropriate approach for this investigation is Dynamic Strategy, as indicated by the results of the comprehensive analytics. For market practitioners, the Dynamic Strategy presents a promising approach, as it generates significantly higher average excess returns than the Momentum, Contrarian, and Ichimoku Strategies. The value of 10,717 clearly exemplifies the advantage of its significant volatility. Market practitioners can profitably optimize their return on investment by utilizing a Dynamic Strategy. However, it is imperative to remember that increased volatility also increases risk similarly. To successfully and sensibly manage risk, market practitioners must have a strong understanding of these strategies.

The momentum path coefficients and contrarian strategies exhibited unexpected and robust direct effects in the opposite direction than anticipated. Relationship Figure A2.1 and Figure A2.2 (Appendix) show the relationship between momentum, contrarian, and dynamic strategies. This shows that price movements follow an "S-curve" shape, which means that prices may go backward and forward around the highs and lows in a short period. Both strategies make a weak contribution to the influence of the dynamic strategy. Even momentum strategies hurt the dynamic strategy's R-square. They raise concerns about potential overfitting, warn against hasty generalizations, and underscore the need to understand the role of noise traders in shaping financial market dynamics. In [41] and [42], he emphasizes the importance of gaining a deeper understanding of market dynamics, which includes recognizing the impact of trader noise and identifying anomalies such as continuation and reversal patterns. The report emphasizes the need to modify trading strategies in response to changing market conditions and warns against wrong conclusions or hasty judgments.

The use of anchoring and representativeness heuristics can introduce ambiguity because they are less consistent in generating continuation patterns and may lead to price movement reversals. Therefore, investors who rely on the highest or lowest levels reached in the last 52 weeks should thoroughly analyze the price movement patterns before making a final investment decision. Errors in predicting proximity to 52-week highs or lows can lead to disposition effects, [43], [44], [45]. As a result, when making trading decisions, traders are often reluctant to use the highest or lowest prices over the previous 52 weeks.

The lack of response to new data as the price approaches the highest (lowest) level in the last 52 weeks is an important element in the continuation patterns [6], [46], [47]. On the other hand, investors often become too optimistic (pessimistic) about stock prospects, [48]. Finally, a correction of this overreaction can change the direction of price movements [8], encouraging confident investors to anticipate a reversal in the long term [15], [16], [49]. Understanding investor behavior and market dynamics is critical to making informed trading decisions.

Figure A2.3 (Appendix) shows a strong positive relationship between Ichimoku's impact on dynamic tactics and the J curve. This shows Ichimoku's ability to detect emerging price trends and provide a significant impact on dynamic trading techniques. The highest and lowest prices over the past 52 weeks indicate an ongoing trend. This price movement trend plays a role in connecting momentum and contrarian strategies with Ichimoku. Furthermore, a developing price movement trend approaching the 52-week high or low level can form a continuation or reversal pattern. Figure A2.4 and Figure A2.5 (Appendix) show the important relationship between momentum and the Ichimoku indicator, resembling an S-shaped curve. In this scenario, the price trend has two reversal points. The Ichimoku indicator functions as a validator that confirms the existence of a positive price trend.

Our results highlight the support of Ichimoku for technical analysis and examine the influence on trading strategies, which provides insight for investors to improve investment decisions, understand market behavior, and show support for dynamic trading strategies like Ichimoku to enhance stock market returns. Since it helps confirm long-lasting patterns of price action, Ichimoku is likely to find favor among dynamic strategy developers, i.e., practitioners and investors alike. Its capacity to send a signal to buy at the onset of a trend and a signal to sell at the termination of a trend makes it an even more important indicator. In other words, Ichimoku provides clearer signals to investors and traders than the noisy moving average approach.

The low R-squared value of the Ichimoku strategy indicates that momentum and contrarian factors explain little of the variance, supporting that its forecasting capabilities are very limited. But when you add it to a momentum strategy, the R-squared is much higher. That is to say, each individual strategy may account for only a small part of the behavior of a market, but together they provide a stronger framework for how and why prices may trend as they do. So, when combined, these approaches will work to enhance its efficiencies in mapping and predicting market trends.

The Kruskal-Wallis test gives us some clues about significant differences in excess returns between different trading techniques (Momentum, Contrarian, Ichimoku, and Dynamic strategies). Performance-wise, the dynamic strategy is able to achieve an optimal average score. The dynamic strategies are statistically different from those of the regulatory strategies. The research underscores the potential effectiveness of combining these tools in novel ways to create creative processes that differentiate their components, with meaningful implications for investors on how best to use them to enhance financial performance. The average score of dynamic strategy is the best which is in accord with its best effect over the entire Quake test protocol. Regulatory strategies differ in principle from dynamic strategies and are statistically different from regulatory strategies

The implications of these findings on research in the further use of heuristics in strategy design to improve earnings are significant. Technical indicators or the Ichimoku could be potential mediators or moderators in this process. These logical heuristics include representativeness and anchoring which can benefit traders when they validate the performance of a trading strategy that they have in their hands, Ichimoku strategies, for example. This streamlines the trading process in real time. The idea of this was that any new perspective on the market could be used to gain a greater insight into how psychological phenomena began to induce further returns in a single act. By validating Ichimoku trading strategies with strategies such as representativeness and anchoring using the enriched techniques of heuristics, traders can check the viability of decisions and build heuristics in a manner that makes them useful as practical tools. This comprehensive approach underscores the importance of integrating psychological insights into investment practices to increase returns. Based on these findings, market bias and fluctuations could influence the 52-week holding strategy, potentially diminishing its long-term effectiveness.

6 Conclusion

A comprehensive examination of four trading strategies about the Indonesian stock exchange is provided: momentum, contrarian, Ichimoku, and dynamic. Through our comprehensive study, we gain vital insights into trading methods and the dynamics of the market. The dynamic approach, which integrates the contrarian, momentum, and Ichimoku techniques, demonstrated superior performance compared to other strategies. Considering the increasing unpredictability and potential for high profits, this underscores the importance of implementing prudent risk management strategies. The important factor is that Ichimoku acts as an intermediary in the relationship between momentum, contrarian techniques, and dynamic methods. It verifies the patterns of price movements and provides timely indicators, which influence the dynamics of the market and improve trading tactics.

This function helps traders make more informed decisions and better navigate the complexities of the market. Understanding market dynamics and adapting strategies is of utmost importance, as our research shows. This underscores the potential dangers associated with overgeneralization and emphasizes the need for a deeper understanding of market anomalies and investor behavior. Furthermore, examining how changing market conditions affect strategy efficacy can provide in-depth information for traders and practitioners.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the authors used Grammarly in order to improve its language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed to the present research at all stages, from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.

Dwi Tjahjo Purnomo,
Sugeng Wahyudi, Harjum Muharam

APPENDIX

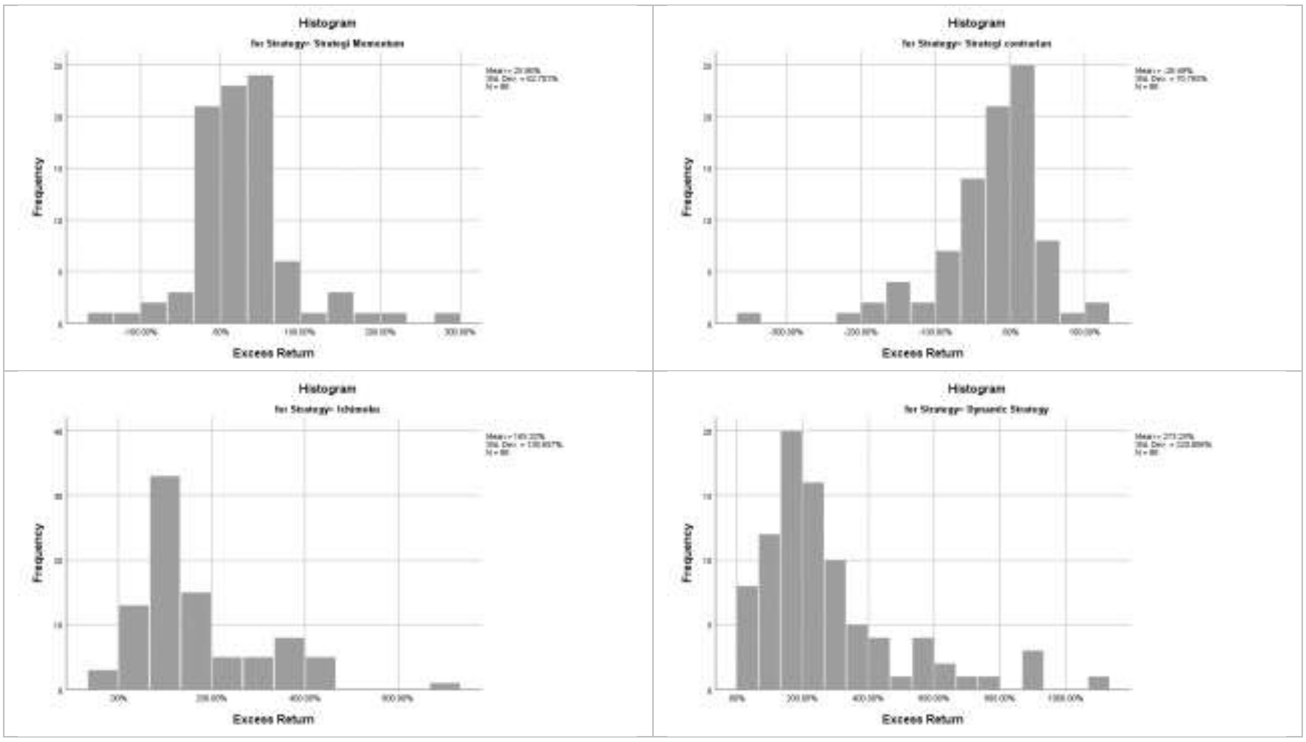
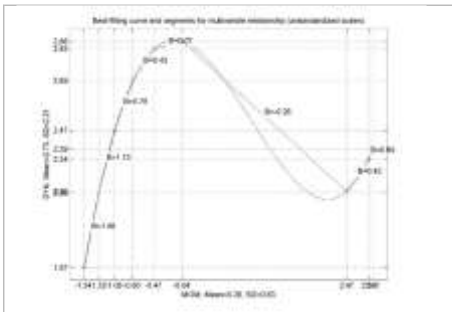
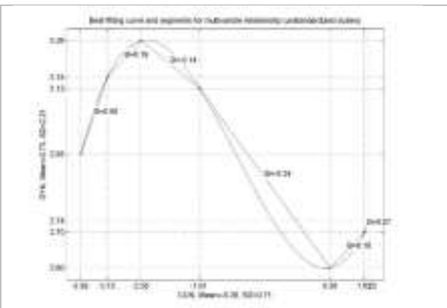


Fig. A1: Histogram the distribution of excess returns across the analyzed strategies



1. a multivariate relationship between MOM→DYN.



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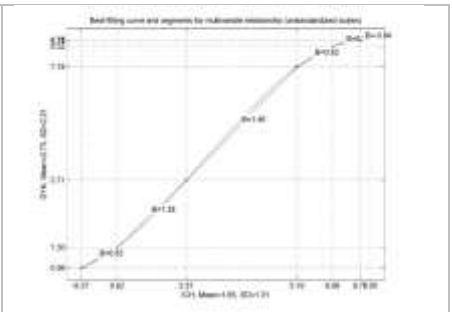
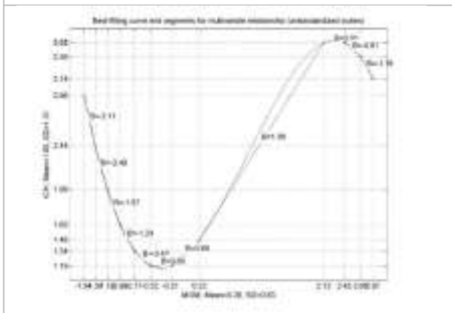
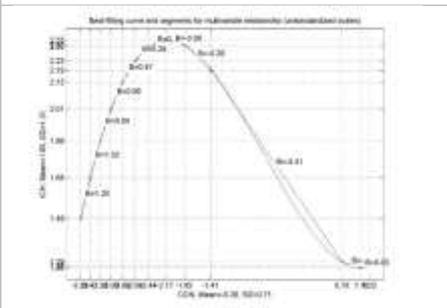


3. a multivariate relationship between ICH→DYN.



4. a multivariate relationship between MOM→ICH.



5. a multivariate relationship between CON→ICH.

Fig. A2: The graph illustrates a multivariate relationship between variables