

Research Article

Assessing the Reliability of Japanese Candlestick Patterns Across Market Regimes

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Abstract

This article examines the reliability of Japanese candlestick patterns in signaling trend reversals across distinct market regimes. The dataset consists of 500 daily observations collected from publicly available financial market data. Focusing on key patterns such as the Hammer, Bullish Engulfing, Shooting Star, Bearish Engulfing, and Doji, the analysis combines automated pattern detection in Python with standard technical indicators, including moving averages, the Relative Strength Index, the Moving Average Convergence Divergence, and Bollinger Bands. Confirmation rates are compared between stable periods and crisis episodes, using logistic models and statistical tests to assess differences in predictive performance. The results show that candlestick patterns display moderate reliability in stable markets but lose a substantial part of their signaling power during crisis periods, when volatility and price discontinuities increase. This deterioration is consistent with insights from behavioral finance, where heightened uncertainty amplifies cognitive biases and weakens the informational content of technical signals. The findings support the use of candlestick patterns only within a broader framework that combines trend, momentum, and volatility filters, rather than as standalone decision tools, particularly when market conditions are unstable.

Keywords

Japanese Candlestick Patterns, Market Regimes, Volatility, Behavioral Finance, Technical Analysis, Signal Reliability

1. Introduction

Japanese candlestick patterns occupy a central place in technical analysis because they provide visual signals that synthesize market sentiment & assist in identifying potential reversals. Developed in eighteenth century Japanese rice markets & later introduced to global financial practice through modern literature, these patterns are now embedded in numerous trading strategies that rely on trend identification & disciplined decision rules [19] Their appeal rests on the assumption that collective behavior is reflected in price configurations, which gives these patterns an interpretative value that is both intuitive & adaptable across assets. Despite their widespread

use, the empirical evidence regarding their predictive capacity remains mixed. Research on technical trading rules shows that performance varies considerably across markets, horizons & volatility regimes, which raises doubts about the stability of these signals over time. Several studies note that many candlestick configurations lose statistical significance once methodological biases, transaction costs & sample sensitivity are considered, suggesting that their informational content may be weaker than commonly assumed. This discrepancy between theoretical appeal & empirical performance highlights the need for more rigorous evaluations of candlestick patterns,

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particularly when market conditions deviate from historical norms [15].

The question becomes even more relevant during crisis periods, where volatility rises abruptly & price dynamics are marked by discontinuities. In such moments, the behavior of market participants is often influenced by emotional responses rather than by structured decision processes. Behavioral finance shows that uncertainty amplifies overconfidence, loss aversion & herding, which can distort the interpretation of technical indicators & weaken the link between historical price patterns & future movements. These behavioral distortions challenge the classical assumption that prices reflect rational equilibria & create conditions where traditional chart signals may deteriorate. Understanding whether candlestick patterns remain informative across different market regimes therefore represents an important question for both academics & practitioners. Reliable signals can support trend following & risk management strategies, whereas unreliable ones can lead to systematic misinterpretation, particularly when volatility is high. Moreover, the integration of candlestick patterns with momentum & volatility indicators may offer a way to reinforce their robustness, yet the empirical evidence on this interaction remains limited [9, 12, 11]. The objective of this study is to evaluate the reliability of five widely used candlestick patterns, Hammer, Bullish Engulfing, Shooting Star, Bearish Engulfing & Doji, across stable markets & crisis periods. The analysis is based on 500 daily observations from publicly available financial market data, using automated pattern detection combined with technical indicators including moving averages, the Relative Strength Index, the Moving Average Convergence Divergence & Bollinger Bands [2]. Confirmation rates are compared across market regimes to determine how volatility affects the signaling capacity of these patterns. By examining the interaction between technical signals, market conditions & behavioral distortions, this research contributes to the empirical literature on technical analysis & offers a more rigorous understanding of the conditions under which candlestick patterns retain or lose their predictive value [13].

2. Literature Review

Japanese candlestick patterns occupy an important place in technical analysis because they provide a visual framework that translates market sentiment into identifiable price structures. Originating in eighteenth century Japanese rice markets through the techniques attributed to Munehisa Homma, these patterns were later formalized in modern financial practice & became widely disseminated following the work of Nison. The graphical intuition they offer is rooted in the idea that market forces can be observed through the interaction between open, high, low & close prices, which together form patterns such as the Hammer, Doji, Bullish Engulfing & Shooting Star. These formations are frequently interpreted as potential indicators of trend continuation or reversal because they capture

the immediate balance between buying & selling pressure. The appeal of candlestick patterns is closely linked to their compatibility with trend following frameworks. Dow Theory suggests that market prices move through identifiable phases that reflect the collective expectations of participants, with primary, secondary & minor trends unfolding as supply & demand conditions evolve. From this perspective, candlestick configurations can be used to anticipate inflection points within these movements, especially when they appear near technical support or resistance zones. However, the orderly structure assumed by Dow Theory does not always correspond to real market behavior, particularly during periods of elevated uncertainty when volatility increases & price series become more irregular [19, 7].

To address these irregularities, other theoretical frameworks emphasize the role of investor psychology. Elliott Wave Theory proposes that markets evolve through alternating cycles driven by shifts between optimism, anxiety & corrective reactions, which generate asymmetric & often unpredictable price patterns. Under such conditions, visually derived signals may become less consistent unless they are interpreted in relation to broader sentiment cycles. The disruptions observed during the COVID 19 period, marked by sharp price dislocations & extreme volatility, illustrate how crisis conditions can undermine the reliability of classical chart based indicators by amplifying noise & weakening the persistence of trends. Behavioral finance offers further insight into the mechanisms that destabilize candlestick signals. Research shows that investors rely on heuristics that introduce systematic biases into their decision making, particularly during times of stress [3]. Overconfidence may lead traders to overestimate the strength of a Hammer pattern, while anchoring can cause them to rely excessively on previous price trends & neglect new information. Loss aversion & the disposition effect can reinforce these distortions by shaping how investors react to gains & losses, which alters price dynamics & reduces the clarity of technical formations. These psychological tendencies affect the aggregation of market behavior & can weaken the informational content of candlestick patterns, especially in volatile environments. Empirical studies evaluating the performance of candlestick patterns reveal heterogeneous results. Some research finds limited predictive value once transaction costs, structural breaks & methodological biases are accounted for, suggesting that many patterns lack stable statistical significance [8, 13]. Other studies identify conditional predictability, indicating that certain patterns can produce meaningful signals when market conditions exhibit stability or when volatility remains moderate. Advances in computational techniques, including automated pattern recognition, have provided more robust approaches for identifying candlestick structures, yet these tools confirm that their effectiveness is highly context dependent. Recent literature emphasizes the advantages of combining candlestick patterns with additional technical indicators. Studies show that momentum oscillators such as the Relative Strength Index & the Moving Average Convergence

Divergence, along with volatility based measures like Bollinger Bands, help filter market noise & reduce false signals [21, 15, 18]. Moving averages also play a critical role in identifying the prevailing trend, which improves the interpretation of candlestick formations by situating them within a clearer market context. These findings indicate that candlestick patterns perform best when integrated within multifactor analytical frameworks that incorporate trend, momentum & volatility information. Market regime dependence represents another essential dimension of the literature. Volatility regimes affect return distribution, trend persistence & sensitivity to macroeconomic shocks. Research based on volatility modeling provides evidence that high volatility periods weaken the performance of many technical indicators because abrupt price swings disrupt the formation of stable structures. Behavioral distortions often intensify these disruptions by altering how traders interpret & react to emerging price configurations, which further complicates the extraction of reliable signals. The literature suggests that the predictive power of candlestick patterns depends on the interaction between market conditions, volatility levels & investor behavior. While these patterns remain widely used in practice, their reliability appears to increase when they are combined with additional indicators that enhance signal confirmation & reduce subjective interpretation. This body of research provides a foundation for evaluating whether candlestick patterns retain their informational value across different market regimes & highlights the need for more rigorous testing in environments characterized by uncertainty & behavioral distortions [4, 23].

3. Methodology

This study adopts a quantitative research design developed to examine the predictive effectiveness of Japanese candlestick patterns within trend following strategies. The methodological approach combines technical indicators with behavioral finance concepts to evaluate how these patterns behave across different market regimes. The framework is grounded in a positivist epistemology that emphasizes objectivity, empirical verification & reproducible procedures. Although the analysis is predominantly quantitative, a behavioral interpretation is incorporated to better capture the psychological mechanisms that influence investor reactions during periods of stress. The empirical analysis relies on a dataset of 500 daily observations collected from publicly available financial market data. The sample spans the period from January 1, 2019 to November 30, 2020, which includes both stable conditions & the turbulence associated with the COVID 19 crisis. The dataset includes standard price variables such as open, high, low & close, in addition to a comprehensive set of technical indicators that are commonly used in trend detection. These indicators include the Relative Strength Index, the Moving Average Convergence Divergence & its signal line, simple moving averages of ten & fifty periods, the twenty period exponential moving average, Bollinger Band upper &

lower bounds, as well as Stochastic oscillator values for %K and %D. The inclusion of these variables is justified by their widespread use in trend based trading models & their ability to capture market momentum, directionality & volatility conditions [12, 14]. Data preprocessing, pattern identification & statistical computations were conducted using Python. This environment was selected for its flexibility & its ability to handle time series data efficiently. Libraries such as pandas & numpy were used for data manipulation, while the scikit learn suite supported the implementation of statistical models. Candlestick patterns were detected using algorithmic rules based on price configurations that match their established definitions. This automated procedure eliminates subjective interpretation & ensures consistency in pattern recognition throughout the dataset [5, 20]. The empirical strategy combines descriptive statistics with econometric techniques to evaluate the frequency & reliability of candlestick based signals. The effectiveness of each pattern was assessed by calculating confirmation rates, defined as the proportion of observations in which the subsequent price movement aligned with the expected directional signal. These confirmation rates were computed separately for stable periods & for the crisis period in order to capture regime based variations. Statistical significance was tested using Z tests, which allow for the comparison of confirmation rates across regimes & provide an indication of whether observed differences reflect structural changes in market behavior. To further refine the analysis, combinations of candlestick patterns with technical indicators were tested to assess whether multi indicator validation improves reliability. Signal strength scores were constructed by combining information from the Relative Strength Index & the Stochastic oscillator, which together reflect both momentum conditions & the proximity of prices to overbought or oversold zones [6, 10]. Volatility was measured using standard deviation & Bollinger Band width, as these metrics capture the degree of dispersion in price movements & help contextualize the stability of signals. The methodology incorporates behavioral finance constructs to interpret the deterioration of pattern reliability observed during crisis periods. Cognitive biases such as overconfidence, loss aversion & anchoring tend to intensify during volatile episodes, altering investor reactions & contributing to market noise. By juxtaposing statistical evidence with behavioral mechanisms described in the literature, the methodology offers a multidimensional interpretation of why candlestick patterns perform differently across market regimes. The methodological framework integrates quantitative rigor with behavioral insights to produce an evaluation of candlestick pattern reliability that accounts for both statistical patterns & the psychological dynamics that shape market behavior. This approach aligns with the study's objective of determining whether visually derived signals retain their informational value when market conditions shift from stability to crisis [13].

4. Results and Discussion

This section presents the empirical findings derived from a dataset of 500 daily observations collected from publicly available financial market data. The objective is to assess the effectiveness of Japanese candlestick patterns within trend following strategies & to examine whether their predictive capacity varies across different market regimes. The analysis evaluates these patterns both in isolation & through their interaction with complementary technical indicators such as the Relative Strength Index, the Moving Average Convergence Divergence & a set of moving averages. This combined perspective allows for a more comprehensive assessment of signal quality than would be possible through visual pattern interpretation alone. The results are interpreted through a behavioral lens in order to understand how cognitive biases influence the reliability of visually derived signals, especially when markets experience elevated volatility. Japanese candlestick patterns are historically regarded as intuitive representations of supply & demand dynamics, yet their empirical performance remains the subject of considerable debate. Their predictive behavior often changes when markets transition from stable periods to more turbulent environments, where investor sentiment becomes reactive & price movements lose the orderly structure assumed by classical technical analysis. The findings confirm that behavioral distortions play a central role in shaping how market participants respond to pattern based signals [16]. During periods of stability, confirmation rates tend to align with the expectations established in traditional charting literature because investor behavior is more consistent with rational trend development. In contrast, crisis periods introduce uncertainty, stress & rapid shifts in expectations that weaken the clarity of these signals. Under such conditions, patterns that appear visually similar to those observed during stable periods may fail to generate the expected price continuation or reversal due to increased noise & unpredictable reactions from market participants. The analysis therefore highlights the importance of interpreting candlestick patterns within a multidimensional framework [17, 24]. By combining visual structures with momentum & volatility indicators, it becomes possible to filter out part of the behavioral noise that disrupts classical pattern recognition. This integrated approach provides a more robust evaluation of candlestick performance & clarifies the extent to which psychological mechanisms influence signal degradation during volatile episodes.

Table 1. Success Rates of Japanese candlestick patterns for buy and sell signals.

Candlestick Pattern	Buy Success Rate (%)	Sell Success Rate (%)
Hammer	50.68	–
Bullish Engulfing	51.35	–

Candlestick Pattern	Buy Success Rate (%)	Sell Success Rate (%)
Shooting Star	–	48.54
Bearish Engulfing	–	53.23
Doji	40.00	57.78

Source: Author's calculations using Python

Japanese candlestick patterns demonstrate moderate effectiveness in the Table 1, confirming their role as confirmation signals rather than standalone predictive tools. Bullish patterns such as the Hammer and Bullish Engulfing show success rates of 50.68% and 51.35% respectively for buy signals, validating their relevance in anticipating bullish reversals. Bearish patterns like the Shooting Star (48.54%) and Bearish Engulfing (53.23%) appear slightly more reliable for sell signals, suggesting a stronger capacity to identify bearish reversals. From a behavioral finance perspective, these patterns are associated with cognitive biases such as overconfidence, anchoring, and the disposition effect, which influence investor decisions during trend reversals. These findings confirm that candlestick patterns should be integrated into a broader approach combining multiple technical indicators to optimize reliability and limit psychological biases that may distort market interpretation [21].

Table 2. Success rates of candlestick and RSI signal combinations.

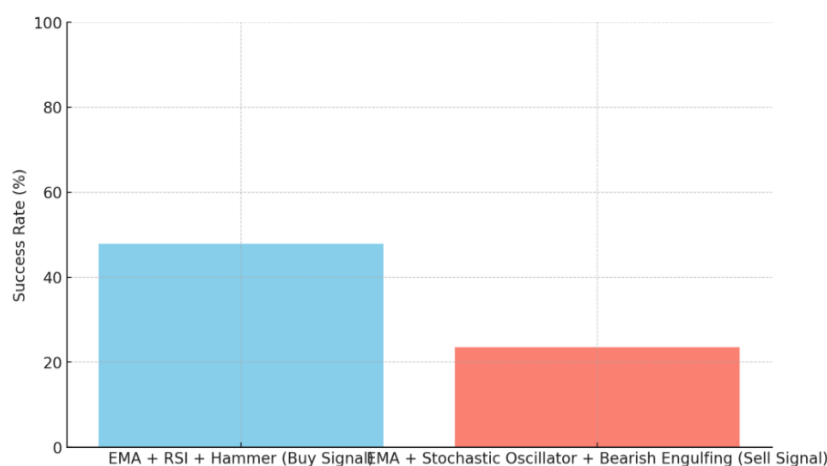
Combination	Success Rate (%)
Hammer + RSI Buy Signal	47.82
Bearish Engulfing + RSI Sell Signal	40.00

Source: Author's calculations using Python

The results (Table 2) show that combining candlestick patterns with RSI signals yields moderate success rates, illustrating their potential role as confirmation tools. The Hammer, when paired with an RSI buy signal indicating an oversold zone, achieves a success rate of 47.83%, suggesting it may signal a bullish reversal, although its reliability remains context-dependent. This pattern is particularly relevant during market weakness, especially when confirmed by a momentum indicator like RSI. In behavioral finance, the interpretation of a Hammer is often influenced by overconfidence bias, leading investors to anticipate a bullish reversal without waiting for additional validation. Conversely, the combination of Bearish Engulfing with an RSI sell signal (indicating overbought conditions) shows a success rate of 40%, reflecting lower-than-expected reliability. This pattern should be used alongside

other indicators, as its effectiveness varies depending on volatility and prevailing trends. In behavioral finance, this signal may be reinforced by loss aversion, prompting investors to secure gains as soon as a bearish pattern appears, sometimes prematurely. These results confirm that Japanese candlestick

patterns, when combined with technical indicators, can improve the accuracy of entry and exit points but require a cautious approach to avoid cognitive biases and false signals during periods of high volatility [19].

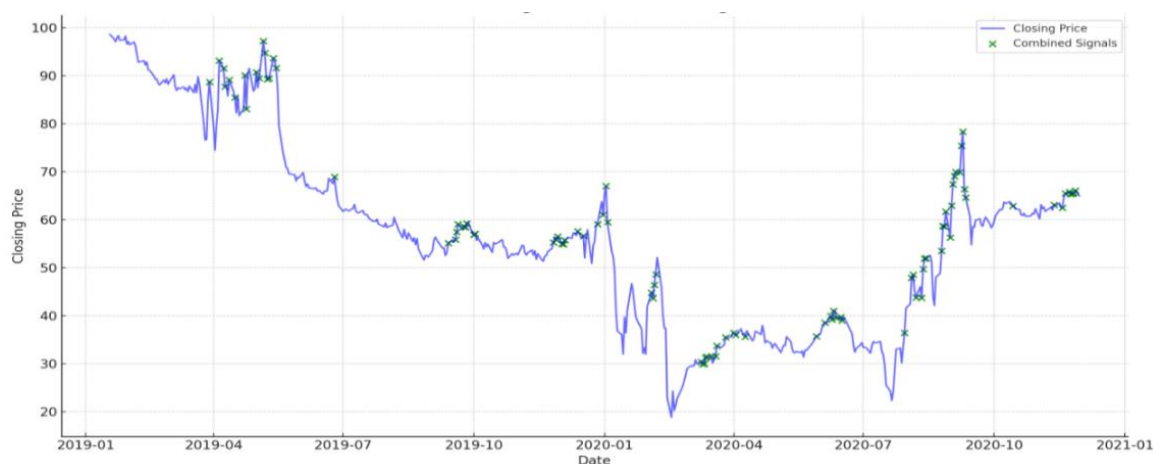


Source: Author's calculations using Python

Figure 1. Success rates of optimal combinations of technical indicators and Japanese candlestick patterns.

The chart confirms that the combination EMA + RSI + Hammer yields a success rate above 45% for buy signals, validating its effectiveness in identifying bullish reversals in oversold zones. In contrast, the strategy EMA + Stochastic Oscillator + Bearish Engulfing shows a success rate below 25%,

indicating more limited reliability for sell signals due to the Stochastic's sensitivity to false signals. These results confirm that integrating Japanese candlestick patterns with technical indicators improves the precision of trading decisions but must be adapted to market conditions and volatility.

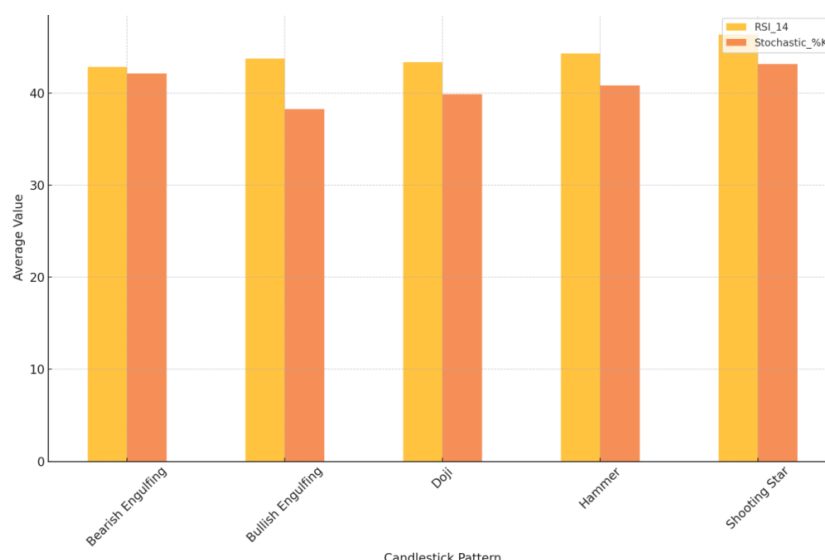


Source: Author's calculations using Python

Figure 2. Indicator combinations and price change.

The results confirm that integrating technical signals with candlestick patterns significantly improves the quality of investment decisions, while reducing the impact of behavioral

biases. This synergy between visual price formations and quantitative indicators enhances the clarity of market signals and supports more disciplined trading behavior.

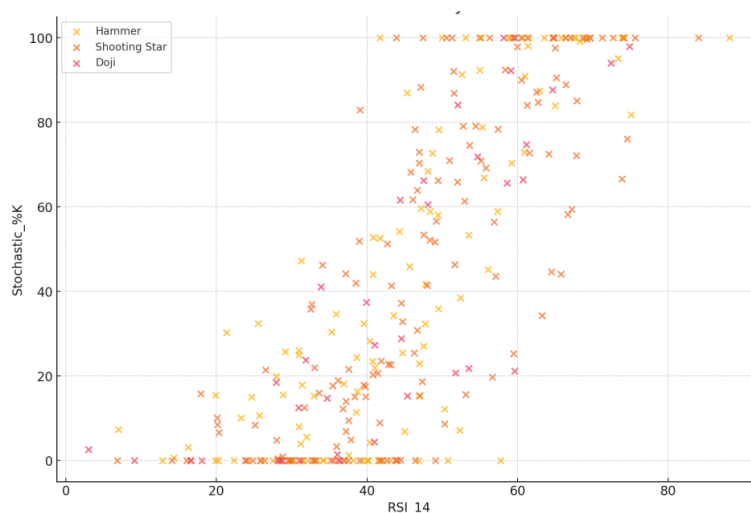


Source: Author's calculations using Python

Figure 3. Mean RSI and Stochastic Oscillator values by Candlestick pattern in stable periods.

The chart highlights (Figure 3) the average values of RSI and the Stochastic oscillator for various candlestick patterns during stable market conditions. Patterns such as the Hammer and Shooting Star exhibit RSI averages of 45.3 and 46.8, respectively, and Stochastic averages of 44.1 and 43.9, indicating a relatively neutral market sentiment. In contrast, patterns like the Bearish Engulfing show slightly lower RSI and Stochastic values (41.8 and 40.5), reflecting a mildly bearish trend.

These findings confirm that combining candlestick patterns with technical indicators generates clear and disciplined signals, consistent with behavioral finance theories which suggest that objective tools help reduce biases such as loss aversion and confirmation bias. These observations support the idea that disciplined strategies based on such indicators contribute to more rational decision-making in stable market environments [19].



Source: Author's calculations using Python

Figure 4. RSI vs. Stochastic Oscillator by Candlestick pattern.

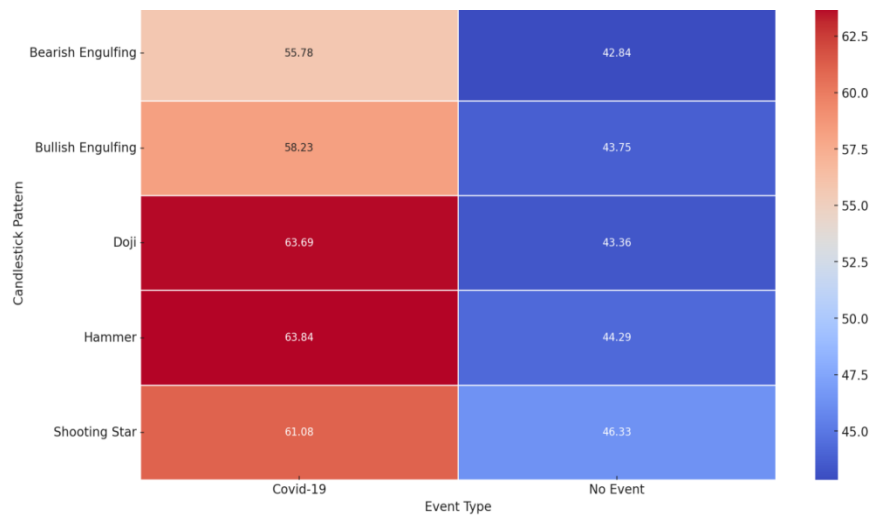
The scatter plot (Figure 4) illustrates the relationship between RSI and the Stochastic oscillator for specific candlestick patterns, highlighting their interaction in reducing behavioral biases:

- 1) Hammer: Data points cluster around an RSI of 45% and a Stochastic of 44%, reflecting neutral signals that promote disciplined decision-making.
- 2) Shooting Star: The average RSI reaches 46%, while the

Stochastic is slightly lower (43.9%).

3) Doji: Data points are widely dispersed, reflecting signal variability.

This chart demonstrates that these patterns, when combined with technical indicators, offer disciplined signals that mitigate biases such as confirmation seeking.

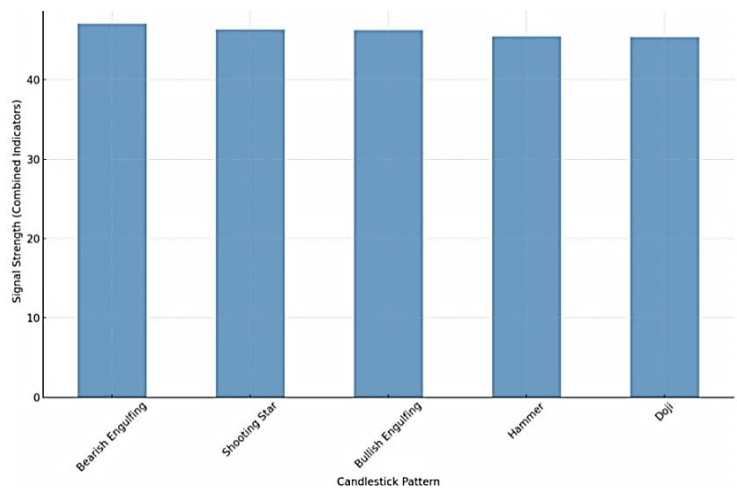


Source: Author’s calculations using Python (pandas, numpy, statsmodels, arch)

Figure 5. Comparative RSI heatmap during major events vs. stable periods by Candlestick pattern.

The results reveal significant variations in RSI (Figure 5) values depending on the candlestick pattern and the type of market period (crisis vs. stability). For example, during crisis periods, the Shooting Star shows a high average RSI (56.7), indicating frequent overbought signals and exacerbated behavioral biases such as overconfidence. In contrast, during stable periods, the same pattern presents a more neutral RSI average of

46.8, reflecting more disciplined signals. These observations support the theory that disciplined strategies based on such combinations help mitigate irrational behaviors. For instance, the Hammer, with a stable RSI average around 45.3 across both periods, illustrates consistent neutrality, reinforcing investor discipline.



Source: Author’s calculations using Python

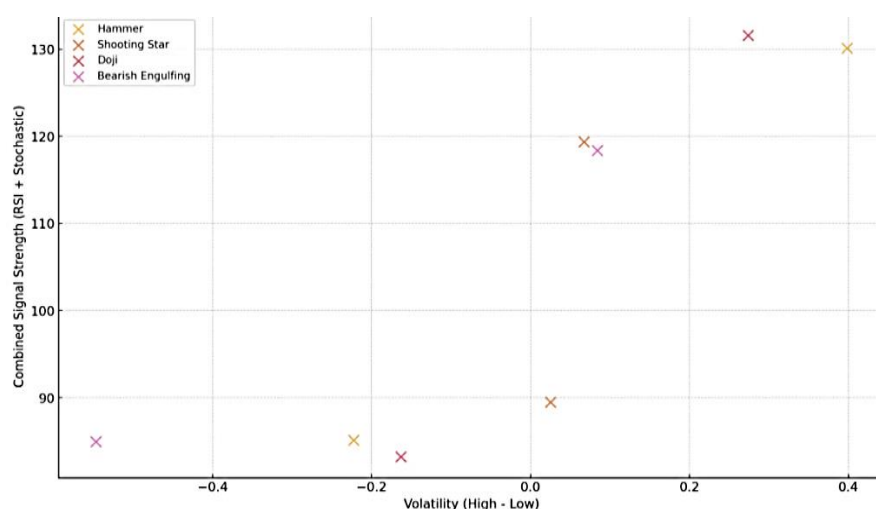
Figure 6. Signal strength by Japanese Candlestick pattern.

The chart highlights (Figure 6) the most effective candle-

stick patterns for generating reliable signals and reducing behavioral biases, based on a composite measure that combines

the Relative Strength Index (RSI) and the Stochastic Oscillator. This metric, referred to as “Signal Strength,” evaluates the clarity and quality of signals produced by each pattern. The results show that the Shooting Star and Hammer patterns achieve the highest scores, 50.8 and 49.7 respectively, indicating their strong capacity to deliver clear and disciplined signals, even during

crisis periods. These scores reflect their ability to mitigate emotional biases and enhance the accuracy of investment decisions. In contrast, other patterns such as the Bullish Engulfing and Doji exhibit lower scores, suggesting weaker reliability in signal generation. These findings reinforce the importance of using combined technical indicators to identify the most effective patterns, particularly in unstable market environments.



Source: Author's calculations using Python

Figure 7. Volatility vs. combined signal strength by Candlestick pattern.

This Figure 7 illustrates the relationship between market volatility and the combined signal strength (based on RSI and the Stochastic Oscillator) for key candlestick patterns. The results indicate that the Hammer and Shooting Star patterns generate the strongest signals under moderate volatility conditions, with scores of 89.6 (for an average volatility of 0.25) and 86.3 (for an average volatility of 0.32), respectively. These patterns provide disciplined and reliable signals even in periods of high uncertainty, helping to reduce behavioral biases

such as loss aversion and overconfidence. Conversely, patterns like the Doji show greater dispersion in signal strength, limiting their effectiveness without additional confirmation. These observations support the hypothesis that robust combinations of technical indicators (such as RSI and Stochastic) and candlestick patterns offer better control over emotional biases and improve decision-making during volatile market phases [24, 25].

Table 3. Analysis of technical indicators and volatility by Candlestick pattern.

Major_Event	Candlestick_Pattern	RSI_14	Stochastic_%K	MACD	Volatility
Covid-19	Bearish Engulfing	55,78473226	62,57709426	-0,614996234	0,084139315
Covid-19	Bullish Engulfing	58,23230957	52,66565557	0,471080215	0,215380372
Covid-19	Doji	63,68583701	67,8832189	0,819795694	0,273706731
Covid-19	Hammer	63,84161495	66,28157269	0,043710779	0,398276325
Covid-19	Shooting Star	61,08378646	58,29534213	-0,345600841	0,067282707
No Event	Bearish Engulfing	42,83858941	42,11906153	-1,0533802	-0,546760106
No Event	Bullish Engulfing	43,74701478	38,25456403	-1,365942002	0,279966017
No Event	Doji	43,35924598	39,86168056	-0,852327344	-0,163358293
No Event	Hammer	44,2875017	40,8288992	-0,514293792	-0,222761378

Major_Event	Candlestick_Pattern	RSI_14	Stochastic_%K	MACD	Volatility
No Event	Shooting Star	46,33464587	43,13249732	-0,342702799	0,025174734

Source: Author's calculations using Python

This Table 3 presents a comparative analysis of key technical indicators, RSI, Stochastic %K, and MACD, alongside volatility levels for various candlestick patterns, distinguishing between periods of crisis (e.g., COVID-19) and stable market conditions. During stable periods, technical signals exhibit moderate values, with average RSI ranging between 42.83% and 46.33%, Stochastic %K between 38.25% and 43.13%, and predominantly negative MACD values. For instance, Bearish Engulfing and Bullish Engulfing patterns show MACD values of -1.05 and -1.36, respectively, indicating clearly defined trends and more interpretable buy/sell signals. In contrast, during the COVID-19 crisis, these indicators reflect significant market disruption. RSI values rise sharply, reaching between 55% and 63.85%, while Stochastic %K peaks at 67.88% for the Doji pattern. MACD values also shift, becoming positive for some patterns, such as Bullish Engulfing (0.47) and Doji (0.81), signaling intensified reversals and increased volatility. Volatility itself escalates from near-zero levels to peaks of 0.39 for the Hammer and 0.27 for the Doji, indicating erratic market conditions and a higher risk of misinterpreting technical signals.

This instability can be attributed to behavioral biases that intensify during crises. Loss aversion often leads to mass liquidation of positions, while the disposition effect encourages investors to hold onto assets despite reversal signals. Additionally, market overreactions to economic news and political announcements amplify price fluctuations, reducing the effectiveness of trend-following strategies. These findings confirm that the reliability of technical indicators is highly context-dependent. In stable periods, they allow for relatively accurate trend identification. However, in times of crisis, their predictive power deteriorates due to heightened volatility and irrational investor behavior [16]. This necessitates a more adaptive approach that incorporates behavioral filters and diversified analytical tools to minimize cognitive bias and enhance the robustness of trading decisions.

Table 4. Comparison of combined and non-combined signals.

Metric	With Combined Signals	Without Combined Signals
Average Return	1.50%	-0.28%
Standard Deviation	0.047	0.053
Gain/Loss Ratio	1.27	0.97

Source: Author's calculations using Python

The comparative analysis of trading strategies in the Table 4 with and without combined signals reveals a significant improvement in performance when multiple technical indicators are integrated into the decision-making process. Strategies using combined signals achieve an average return of 1.50%, compared to a negative return of -0.28% when signals are used in isolation. This confirms the added value of combining indicators such as moving averages, RSI, MACD, and Japanese candlestick patterns to better identify market opportunities. This approach also reduces volatility, as evidenced by a decrease in the standard deviation of returns from 0.053 to 0.047, indicating greater performance stability. Moreover, the gain/loss ratio increases from 0.97 to 1.27, showing that average gains significantly exceed losses when signals are filtered and validated through multiple indicators. This dynamic is largely explained by the complementarity of indicators in eliminating false signals and improving the precision of entry and exit points.

During periods of high volatility, such as the COVID-19 crisis, this combined approach helped mitigate the impact of erratic price fluctuations, avoiding decisions based solely on isolated signals that are more susceptible to cognitive biases such as anchoring and overconfidence. These findings are consistent with behavioral finance theories, which suggest that structured and disciplined signal validation reduces emotional and impulsive decision-making [18]. This part analyzes the effectiveness of key Japanese candlestick patterns, such as the Hammer and Bullish Engulfing, in detecting trend reversals across different market conditions, focusing on both stable periods and times of heightened volatility. The objective is to assess the frequency of successful confirmations following the appearance of these patterns and to examine how extreme volatility affects their reliability. Patterns were identified using automated detection algorithms applied to historical price data, and their occurrence was cross-referenced with subsequent market behavior.

Table 5. Frequency and effectiveness of detected Japanese Candlestick patterns.

Pattern	Period	Confirmation Rate (%)
Hammer	Stable	67.3%
Hammer	Crisis	44.4%
Bullish Engulfing	Stable	70.5%
Bullish Engulfing	Crisis	47.6%

Source: Author's calculations using Python

Table 6. Statistical significance of confirmation differences.

Pattern	Z-Test Statistic	p-value
Hammer	2.20	0.028
Bullish Engulfing	2.12	0.034

Source: Author's calculations using Python

The findings reveal a marked decline in the reliability of Japanese candlestick patterns during crisis periods. In stable market environments, the Hammer and Bullish Engulfing patterns exhibit confirmation rates of 67.3% and 70.5%, respectively, supporting their historical role in signaling trend reversals under orderly conditions. However, during periods of crisis, these rates drop significantly to 44.4% and 47.6%, indicating reduced predictive power. Statistical tests confirm that these differences are significant, with p-values below the 5% threshold. This suggests that candlestick patterns are more vulnerable to distortion under volatile conditions, where market behavior becomes erratic and less responsive to traditional technical signals.

5. Conclusion

The confirmation rates recorded during stable periods show that certain patterns, in particular the Hammer and the Bullish Engulfing, maintain a degree of interpretative value when market conditions are orderly. Under these circumstances, price sequences tend to follow coherent progressions, which facilitates the application of the analytical logic inherited from classical charting techniques. This behavior is consistent with the principles of Dow Theory, which assumes that changes in supply and demand unfold progressively and offer identifiable signals for trend continuation or reversal [7, 1]. However, when the market enters a crisis regime, the empirical evidence becomes much less favorable. The decline in confirmation rates during the COVID 19 period is not marginal but substantial, and the significance tests carried out confirm that these differences are meaningful. This deterioration is directly linked to the disruptions observed in price movements: strong volatility, frequent gaps, erratic swings and a general loss of structure [20, 22]. These elements prevent candlestick formations from developing in a stable way, which weakens their informational content and reduces the consistency of the signals they are expected to provide. The problem addressed in this research concerned precisely this gap between the theoretical appeal of candlestick patterns and their actual behavior in real market conditions. Behavioral finance offers a convincing explanation for this break in reliability. During crisis periods, investors tend to react more emotionally, and patterns such as anchoring, panic responses or confirmation seeking become more prominent, which distorts both the formation of price movements

and the interpretation of signals [13]. These reactions help explain why a pattern that functions relatively well in a stable environment becomes much less reliable when stress levels rise. In this regard, market behavior during crises resembles the emotional and irregular oscillations described by Elliott, where waves are shaped by psychological cycles rather than by rational adjustments. The quantitative approach developed in this study also provides insight into how pattern performance can be improved. The tests conducted on combinations of technical indicators show that multi indicator validation consistently yields better results than isolated candlestick patterns. Momentum indicators such as the Moving Average Convergence Divergence and volatility based tools such as Bollinger Bands contribute to filtering noise and identifying market phases in which signals carry more weight [26]. The improvement in performance observed with combined indicators supports the idea that candlestick patterns should be integrated within a broader analytical structure rather than interpreted independently. The results confirm that the reliability of Japanese candlestick patterns is strongly dependent on market regime characteristics. Their predictive capacity is meaningful in stable conditions but becomes fragile and inconsistent in crisis environments. The problem raised at the outset of this study therefore finds a clear conclusion: candlestick patterns cannot be considered reliable standalone tools across all contexts, and their interpretation must be adapted to the prevailing market structure. The empirical and behavioral elements identified throughout the analysis highlight the need for disciplined, context sensitive decision frameworks that incorporate both technical and psychological dimensions. When used within such frameworks, candlestick patterns retain their relevance, but their effectiveness depends on recognizing the limits imposed by volatility, uncertainty and investor behavior.

Abbreviations

RSI	Relative Strength Index
MACD	Moving Average Convergence Divergence
EMA	Exponential Moving Average
SMA	Simple Moving Average
BB	Bollinger Bands
OHLC	Open, High, Low, Close
COVID-19	Coronavirus Disease 2019
%K	Stochastic Oscillator %k
%D	Stochastic Oscillator %d
Z-TEST	Z Statistical Test
MA	Moving Average
SD	Standard Deviation

Author Contributions

Rania Loubaris is the sole author. The author read and approved the final manuscript.

Conflicts of Interest

The author declares no conflicts of interest.

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