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Technical indicators under pressure: Performance and limitations in the face of market shocks.

Indicateurs techniques sous pression : Performance et limites face aux chocs du marché

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Abstract:
This article examines the impact of geopolitical events on the reliability of technical indicators commonly used in trend-following strategies. Using a database composed of daily series from several financial assets, covering the period from January 2019 to November 2020, the study compares the behavior of indicators such as SMA_50, EMA_20, RSI_14, MACD, and Stochastic %K between stable market conditions and periods of crisis, particularly those related to the Covid-19 pandemic. The analysis, carried out using Python, reveals a marked deterioration in signal quality during periods of crisis: moving averages become less responsive, the MACD loses consistency, and oscillators such as the RSI display excessive volatility, which can generate false signals. Internal correlations between indicators are also altered, suggesting a break in the usual technical dynamics. A simple regression confirms the significant effect of volatility on the trend, as measured by the SMA_50.

Keywords: technical indicators, financial markets, volatility, geopolitical crises, quantitative analysis.

Résumé :
Cet article examine l'impact des événements géopolitiques sur la fiabilité des indicateurs techniques couramment utilisés dans les stratégies de suivi de tendance. À l'aide d'une base de données composée de séries quotidiennes de plusieurs actifs financiers, couvrant la période de janvier 2019 à novembre 2020, l'étude compare le comportement d'indicateurs tels que SMA_50, EMA_20, RSI_14, MACD, et Stochastic %K entre des conditions de marché stables et des périodes de crise, notamment celles liées à la pandémie de Covid-19. L'analyse, réalisée à l'aide de Python, révèle une nette détérioration de la qualité des signaux en période de crise : les moyennes mobiles deviennent moins réactives, le MACD perd de sa consistance et les oscillateurs tels que le RSI affichent une volatilité excessive, ce qui peut générer de faux signaux. Les corrélations internes entre les indicateurs sont également modifiées, ce qui suggère une rupture de la dynamique technique habituelle. Une régression simple confirme l'effet significatif de la volatilité sur la tendance, mesurée par la SMA_50.

Mots clés : indicateurs techniques, marchés financiers, volatilité, crises géopolitiques, analyse quantitative

Introduction

In times of stability, financial markets follow relatively predictable dynamics that technical indicators can often anticipate effectively. Moving averages, oscillators, volatility bands: these tools have become central to the trend-following strategies adopted by professional and individual investors alike. These instruments are based on the assumption that market behavior repeats itself, that trends can be detected, and that rational decisions dominate price fluctuations. However, this well-oiled machine breaks down abruptly when major exogenous events occur. Geopolitical, health, or economic crises act as catalysts for instability: they disrupt normal cycles, amplify volatility, and trigger collective emotional reactions. In these critical moments, technical indicators, designed to function in a relatively orderly environment, reveal their limitations. Signals become ambiguous, crossovers multiply without clear direction, and overbought or oversold zones expand without apparent fundamental justification. This article addresses the question: what happens to technical indicators when the market enters a period of turbulence?

More specifically, we analyze the impact of geopolitical events, particularly the Covid-19 pandemic, on the behavior of several iconic technical indicators such as the RSI, MACD, Stochastic, SMA, and EMA. By cross-referencing market data covering the period from January 2019 to November 2020 with robust statistical models, we seek to understand how these tools change in a crisis context: do they become too sensitive? Too slow? Do they lose their internal consistency?

Our central hypothesis is that the effectiveness of technical indicators is contextual: it varies significantly depending on the level of uncertainty and the nature of exogenous shocks. Through a rigorous quantitative approach, this study highlights the structural flaws that emerge in periods of instability, while proposing avenues for methodological adjustment. The objective is not to question technical analysis as a whole, but to better identify its areas of fragility in order to encourage a more nuanced and adaptive reading of market signals. By combining empirical data, trend theories (Dow, Elliott) and contributions from behavioral finance, this research aims to enrich our understanding of the limitations of classical technical models in the face of the unpredictability of contemporary crises.

1. Literature review: Technical analysis put to the test in times of crisis

Technical analysis is based on a key assumption: market prices reflect all available information and evolve according to repetitive patterns and identifiable trends (Murphy, 1999). This approach, which relies on observing the past to anticipate future movements, differs from fundamental analysis in that it focuses on internal market dynamics rather than exogenous economic variables. It uses a variety of graphical and statistical tools to identify entry and exit signals. Among the most commonly used are moving averages (SMA, EMA), momentum indicators such as MACD or RSI, and Bollinger bands, which measure implied volatility. These technical indicators can be used to assess the direction and strength of a trend, detect potential reversal zones, or confirm an already initiated signal. However, their effectiveness depends on a relatively orderly market environment, in which the behavior of market participants follows stable and rational logic (Neely, Weller & Ulrich, 2009). In other words, the predictive power of technical indicators is conditioned by a certain degree of structural stability.

However, this stability is regularly challenged by exogenous events such as economic crises, geopolitical tensions, and pandemics. These shocks disrupt the usual market cycles, leading to increased volatility, erratic movements, and a loss of trend clarity (Han, Yang, & Zhou, 2016). Under these conditions, technical signals can become ambiguous or even contradictory. An indicator such as SMA_50, generally used to confirm long-term trends, becomes too slow to react to sudden reversals, as shown by empirical analysis conducted during the Covid-19 crisis. Similarly, the MACD can lose consistency when price movements become desynchronized or overly compressed around unstable levels. These observations are consistent with the criticism expressed in the literature on the fragility of technical models in the face of nonlinear instability. When markets no longer follow smooth trajectories but react to unexpected emotional, political, or structural dynamics, the validity of signals from technical analysis is weakened. This justifies the need for a contextual reading of indicators and, in times of crisis, a methodological adjustment aimed at strengthening their robustness.

1.1 Geopolitical shocks and market behavior: toward nonlinear instability

Geopolitical events, due to their sudden and exogenous nature, profoundly disrupt the structure of financial markets. Unlike predictable economic cycles or expected technical variations, geopolitical crises create informational discontinuities, spikes in volatility, and disruption in investment behavior. The literature highlights that these periods of disruption produce erratic price movements that are poorly correlated with economic fundamentals, making forecasting particularly difficult (Baker, Bloom & Davis, 2020).

The Covid-19 pandemic is a prime example of this. Numerous studies have demonstrated a sharp increase in volatility, accompanied by a contraction in volumes and excessive reactivity on the part of market participants (Fahlenbrach et al., 2021; Mazur, Dang & Vega, 2021). These collective reactions are part of a non-linear dynamic, where prices no longer follow a sequential or cyclical logic, but adjust sharply to announcements, rumors, or political measures. The market then becomes a theater of panic or wait-and-see attitudes, where rational decisions are often supplanted by emotional biases such as loss aversion or herd behavior (Barberis, Shleifer & Vishny, 1998; De Bondt & Thaler, 1985).

These exaggerated behaviors result in a significant alteration of technical signals. Moving average crossovers, which usually indicate structured reversals, lose their reliability in disorderly environments. Momentum indicators generate skewed signals, and oscillators display extreme levels without fundamental justification. In a crisis context, technical indicators no longer reflect market dynamics alone, but also become reflections of the collective emotions that permeate them (Shiller, 2003).

1.2. Conditional resilience of technical indicators

Far from being universally reliable, technical indicators show conditional effectiveness, which is highly dependent on the market context. In stable periods, their ability to detect trends, anticipate reversals, or confirm signals is well documented and widely validated (Murphy, 1999; Neely et al., 2009). But in times of crisis, these same indicators lose their relevance, requiring critical interpretation and methodological calibration.

Moving averages illustrate this limitation well. While the SMA_50 is often used as a benchmark for underlying trends, its inertia becomes problematic in periods of rapid reversal. Conversely, the more sensitive EMA_20 reacts more quickly but produces a series of noisy signals that are difficult to interpret (Bouchaud, Farmer & Lillo, 2009; Han, Yang & Zhou, 2016). Empirical analysis conducted over the 2019–2020 period confirms this duality: in times of crisis, the SMA shows a significant average decline and a loss of consistency with the RSI, while the EMA shows an unstable correlation, reflecting contradictory signals. The MACD, meanwhile, loses its ability to capture momentum reversals. During the pandemic, its average tends towards zero, betraying a neutralization of the signal, whereas in stable periods it shows a strong correlation with the RSI (up to 0.71), confirming its usefulness in an orderly environment.

Oscillators such as the RSI_14 or Stochastic_%K are no exception. Designed to identify overbought or oversold areas, they become hypersensitive in times of stress, reaching extremes that are not justified by fundamental market developments. This overreaction, linked to investors' behavioral biases, generates a series of false signals which, if not corrected, can lead to erroneous decisions (Kahneman & Tversky, 1979; Shiller, 2003). In this context, the literature recommends a combined and cross-referenced use of indicators to filter out anomalies and reinforce the robustness of signals (Prechter, 2002; Bekaert, Hoerova & Duca, 2022). Thus, the performance of technical indicators is neither constant nor absolute. It depends closely on the market regime in which they are used. Their resilience is contextual: in a stable environment, their effectiveness is proven; in a crisis context, their reliability is weakened, requiring adaptation of models and increased vigilance in interpreting signals.

1.3. Contributions of cycle and behavior theories

Classic theories of stock market cycle analysis provide essential interpretive frameworks for understanding the chaotic dynamics of markets in times of crisis. Two approaches dominate this structural interpretation: Dow theory and Elliott wave theory. Both enable the analysis of trend formation and reversal, taking into account the correction phases and reversal signals often observed in times of extreme turbulence. Dow Theory, founded in the late 19th century and systematized by Hamilton (1922), distinguishes between three types of trends: the primary trend, secondary trends (corrections), and minor fluctuations. In times of crisis, this structure becomes more difficult to perceive, as secondary movements intensify and can mask the underlying trend. Your empirical analysis of the Covid-19 period validates this observation: daily returns show a sharp alternation of rises and falls, making the main trends unreadable, as indicated by the frequent crossovers between the SMA_10 and EMA_20. In line with Dow, Elliott's wave theory (Prechter, 2002) offers a fractal view of markets, based on the alternation of impulsive and corrective waves. This theory makes perfect sense in a crisis context, where corrective waves can be amplified by exogenous factors, leading to unexpected reversals. Your results show that volatility peaks around ±0.3 on returns can be interpreted as major turning points in the wave cycle. The MACD and RSI, although traditionally used to confirm these reversals, lose accuracy here, highlighting the difficulty of mechanically applying Elliott's principles in a context of prolonged instability.

Alongside these structural approaches, behavioral finance provides a complementary interpretation focused on cognitive biases. In crisis situations, investors do not react solely to fundamentals or trends, but are guided by emotions such as fear, panic, or overconfidence.

These biases alter the supposed rationality of markets and contribute to the creation of erratic movements (Kahneman & Tversky, 1979; Shiller, 2003). Your empirical data reveal this drift: the RSI reaches extreme levels in times of crisis, reflecting a collective overreaction that is difficult to justify by economic data alone. Thus, technical indicators become mirrors of collective behavior as much as tools for analysis. Their effectiveness therefore depends not only on the quality of the signal they produce, but also on the analyst's ability to interpret its meaning through an emotional and contextual lens. This hybridization between cyclical models and behavioral interpretation provides a better understanding of why, in times of shock, traditional signals become ambiguous, and why technical analysis then needs to be rearticulated with more qualitative and adaptive approaches.

2. Research methodology

This article is based on a quantitative approach aimed at assessing the impact of major geopolitical events on the effectiveness of technical indicators used in trend-following strategies. The objective is to identify the extent to which these tools, which are usually reliable in stable periods, are weakened in unstable market contexts characterized by increased volatility and heightened emotional behavior.

The data used covers the period from January 1, 2019, to November 30, 2020. It was extracted from a professional trading platform (name confidential) and relates to a representative financial asset. The sample comprises 500 daily observations, including opening and closing prices, daily extremes and volumes, as well as a set of calculated technical indicators: SMA_50, EMA_20, RSI_14, MACD, Stochastic %K and %D, and Bollinger Bands. The processing was carried out in Python, using the pandas, numpy, seaborn, and matplotlib libraries. The analysis consists of four parts:

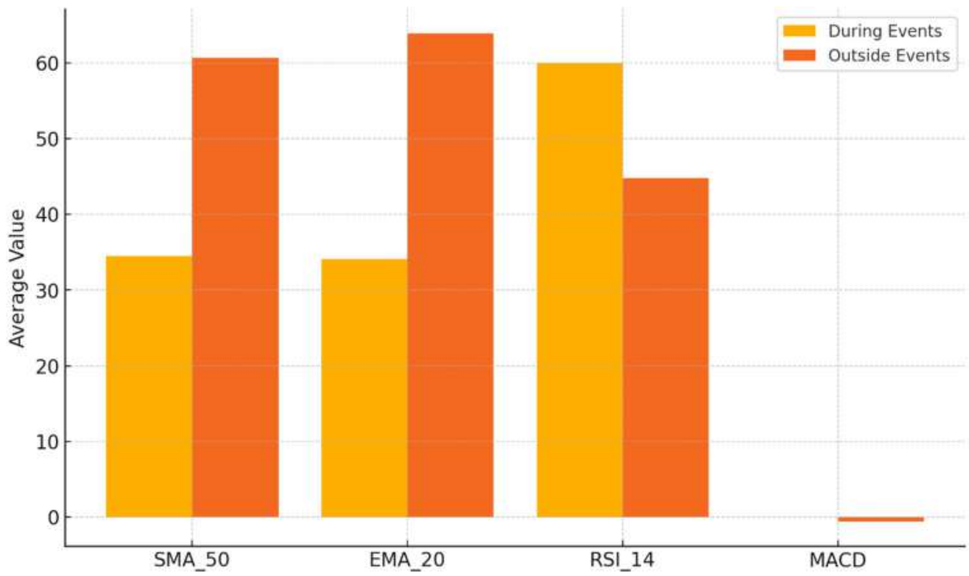
- Comparison of the averages of technical indicators between normal periods and crisis periods, in order to detect behaviors specific to instability;
- Calculation of cross-correlation coefficients between RSI_14 and other indicators (MACD, SMA_50, EMA_20, Stochastic %K) to assess breaks in internal consistency according to context;
- Estimation of a simple linear regression model, taking SMA_50 as the dependent variable, with two explanatory variables: a dummy variable representing crisis periods and RSI_14 as a proxy for volatility;
- Graphical visualization of the results through time series figures, comparative box plots, and correlation matrices, illustrating signal distortions and structural changes in the indicators.

3. Results and discussion

Markets speak to us, but their language changes when storms are brewing. This study delves into a paradox: how do technical indicators, those faithful companions of traders, transform in the face of geopolitical crises?

The data reveals a fascinating metamorphosis, the tools that usually guide our decisions become, in turn, fragile compasses and mirrors of our emotional excesses.

Figure 1: Moving averages, RSI, and MACD during event periods vs. normal periods

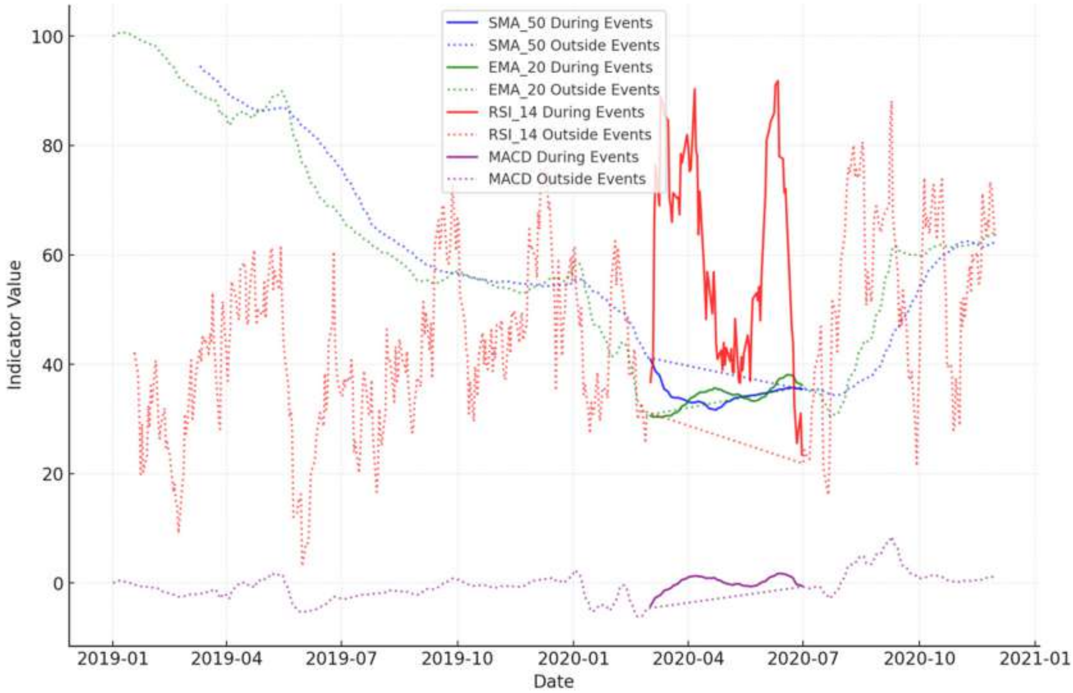


Source : Python

The results show a significant disruption in technical indicators during periods of geopolitical events, validating the hypothesis that these events make trend-following strategies less reliable. Moving averages (SMA_50 and EMA_20) show significantly lower average values (~34% versus ~60% outside of events), indicating increased trend instability.

The RSI_14 is higher during crises (59.94% vs. 44.73% outside of events), suggesting phases of overvaluation and unusual volatility. The MACD, a momentum indicator, becomes less reliable, with an average close to zero (0.03) compared to -0.63 in normal times, signaling a loss of consistency in trend signals. These results highlight the impact of crises on technical indicators, requiring methodological adjustments to better integrate volatility and limit false signals in times of uncertainty.

Figure 2: Temporal evolution of key indicators during and outside events



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Empirical analysis highlights a significant deterioration in the reliability of technical indicators during periods of geopolitical crisis, confirming the hypothesis that such events negatively affect trend-following strategies. Increased uncertainty and volatility make markets less predictable, thereby increasing the risk of error in traditional technical models. False signals are generated by trend indicators, particularly SMA and MACD, which struggle to keep up with erratic and non-linear price movements. These indicators, which are usually effective in stable market conditions, become too slow to adjust to rapid reversals, making them difficult to use for anticipating significant movements. At the same time, experts insist on the need to integrate a more comprehensive approach, combining fundamental and technical analysis, to avoid errors associated with purely quantitative models. Indeed, during crises, market decisions are often influenced by exogenous factors (political announcements, economic instability, emotional reactions from investors) that are not captured by traditional algorithmic models. This analysis also highlights an overreaction by oscillators such as the RSI, which records abnormally high peaks during periods of crisis, overestimating overbought or oversold conditions and thus generating false signals.

These results confirm that markets behave non-linearly during periods of instability, rendering strategies based solely on technical indicators ineffective. Investors must therefore adjust their analysis models by incorporating more dynamic tools capable of taking volatility and exogenous events into account in order to avoid making erroneous positions. This study empirically and theoretically validates that geopolitical events profoundly alter the structure of financial markets, requiring a more cautious and flexible approach to effectively adapt to periods of instability.

Table 1: Correlation of technical indicators during and outside of COVID-19

Indicateur	Corrélation avec RSI durant Events	Corrélation avec RSI hors Events
SMA_50	0,062642761	-0,235632883
EMA_20	-0,217858301	-0,070343114
MACD	0,262614536	0,708090251

Source : Python

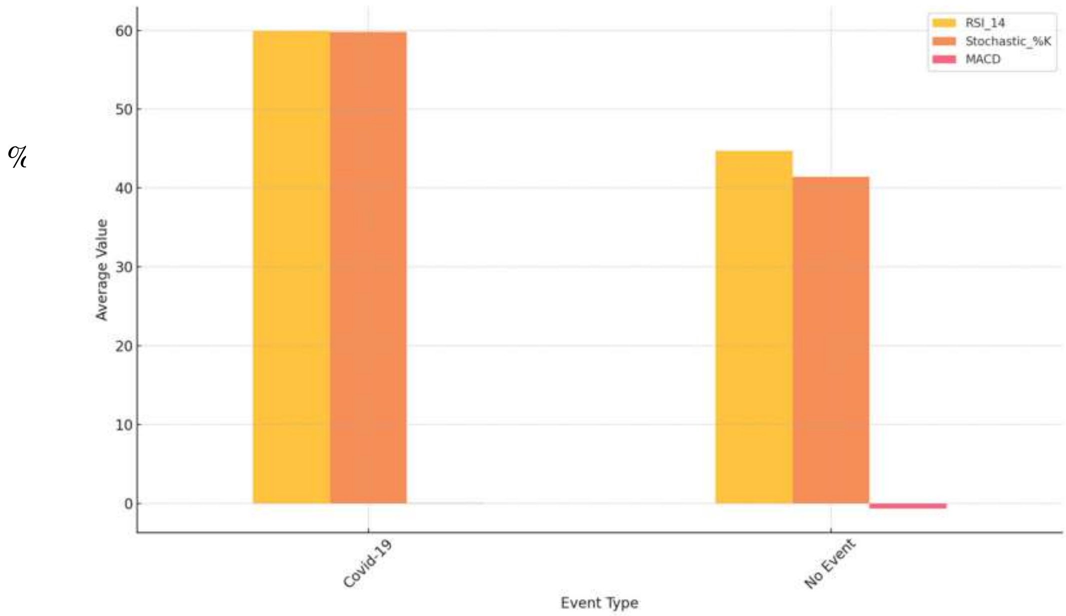
The results show that the correlation between technical indicators and the RSI varies considerably depending on the market context. During geopolitical events, the SMA_50 shows a weak positive correlation (0.062), indicating that moving averages remain relatively insensitive to increased volatility, which limits their effectiveness in times of crisis. The EMA_20, with a slightly negative correlation (-0.218), reflects instability in identifying short-term trends, making its signal more erratic. The MACD, meanwhile, shows a moderate correlation with the RSI (0.263), suggesting some responsiveness to market fluctuations, although this relationship is significantly stronger outside of crises. Outside of geopolitical events, the SMA_50 shows a negative correlation (-0.236), confirming that long trends are more reliable in stable market conditions. The EMA_20, with a correlation of almost zero (-0.070), shows that it is less influenced by RSI fluctuations outside of crises, reflecting relative neutrality. On the other hand, the MACD has a strong positive correlation (0.708) with the RSI, confirming that momentum closely follows market variations in stable periods but loses effectiveness in the face of more unpredictable fluctuations in times of crisis.

These results validate the hypothesis that technical indicators react differently depending on the volatility context, reinforcing the idea that in times of crisis, strategies based purely on trend following must be adapted to avoid false signals and better capture market reversals. Statistical analysis confirms a significant negative impact of geopolitical events and volatility on the performance of technical indicators, particularly the SMA_50.

The effect of crises is marked by a coefficient of -23.73 ($p < 0.001$), indicating an average decline of 23.73 units in the SMA_50 during these periods, highlighting the increased instability of trends. The effect of volatility (RSI_14) is also negative (-0.181, $p < 0.001$), showing that each one-unit increase in volatility reduces the SMA_50 by 0.181 units, confirming that trends become less reliable when volatility is high.

The intercept of 69.03 indicates that, outside of crises and in the absence of extreme volatility, the SMA_50 is relatively stable. However, the R^2 of the model (0.361) suggests that only 36.1% of the variability in the SMA_50 is explained by these variables, implying the existence of other factors influencing market trends. These results validate the hypothesis that geopolitical events and volatility undermine the reliability of trend-following strategies, requiring technical analysis models to be adapted to better manage unstable conditions.

Figure 3: RSI, Stochastic, and MACD during and outside of Covid-19.

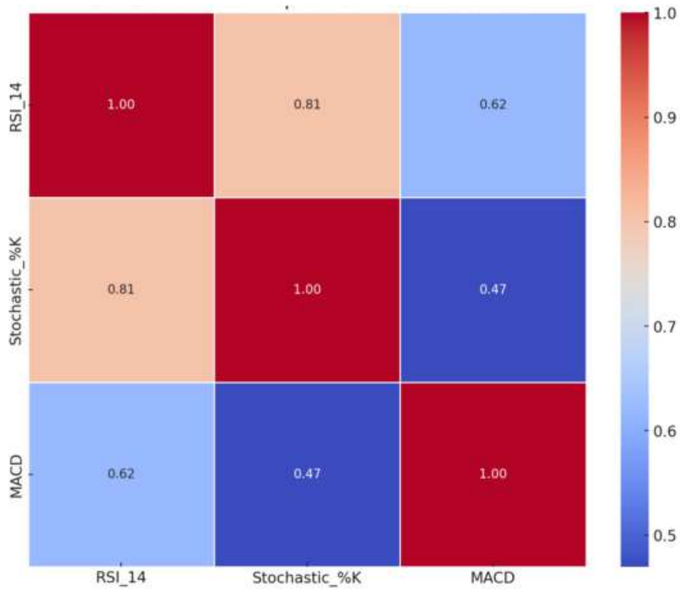


Source : Python

This chart highlights the significant differences between periods of major crises and stable periods in terms of the behavior of technical indicators. During periods of crisis, such as Covid-19, the RSI_14 and Stochastic_%K reach high averages (around 60%), reflecting markets with high probability and frequent overbought signals. In contrast, during stable periods, these values are more moderate, around 45%, indicating a balanced market that is less susceptible to emotional biases. Expert responses corroborate these observations, highlighting that crises accentuate behavioral biases, particularly loss aversion and overconfidence, due to extreme technical signals.

They recommend a combination of indicators to clarify decisions, which is confirmed by the results showing that the MACD is much more stable (close to zero) during stable periods, facilitating greater discipline in investment strategies. These results support the theoretical idea that combinations of technical signals (such as the RSI and MACD) are particularly crucial during crises to reduce the impact of biases and provide clear signals.

Figure 4: Correlation between RSI, Stochastic %K, and RSI 14



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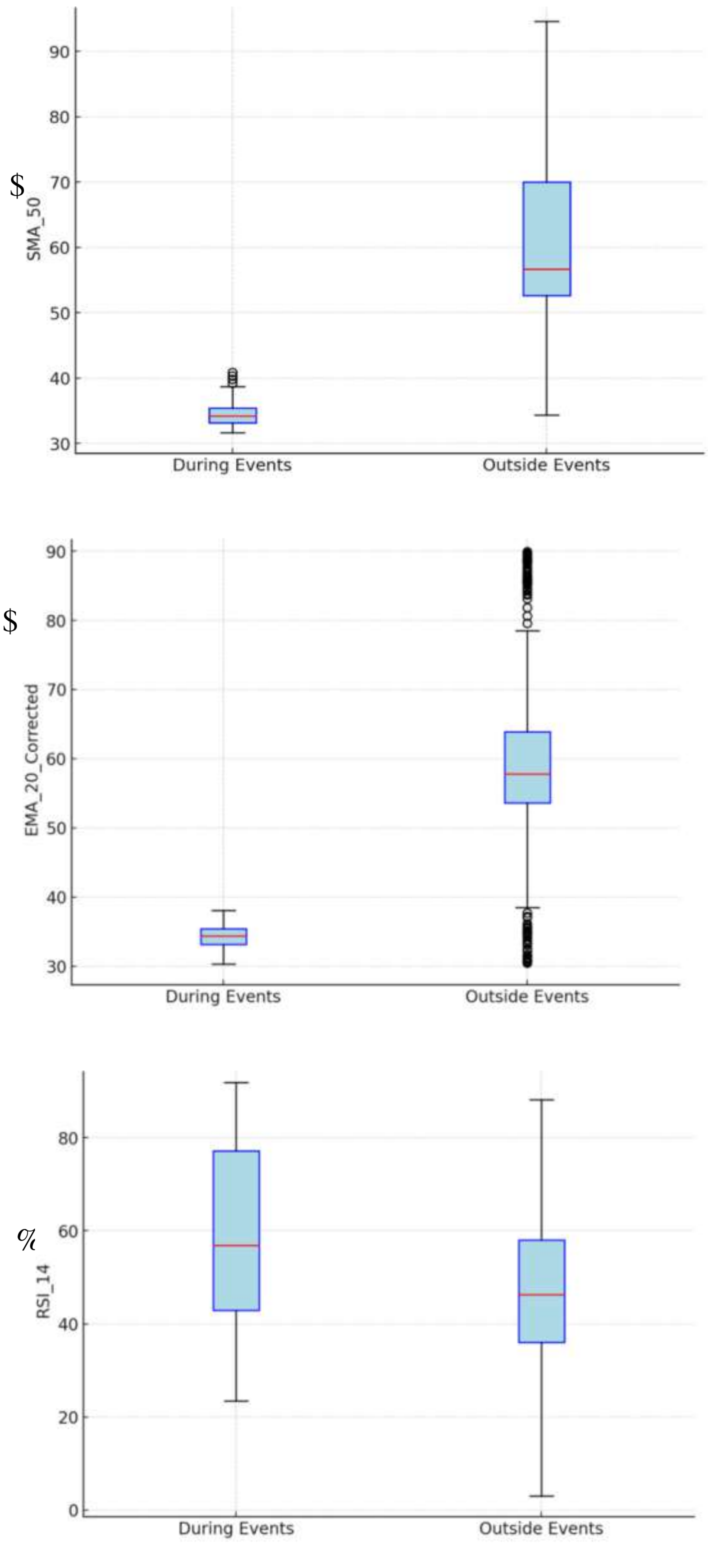
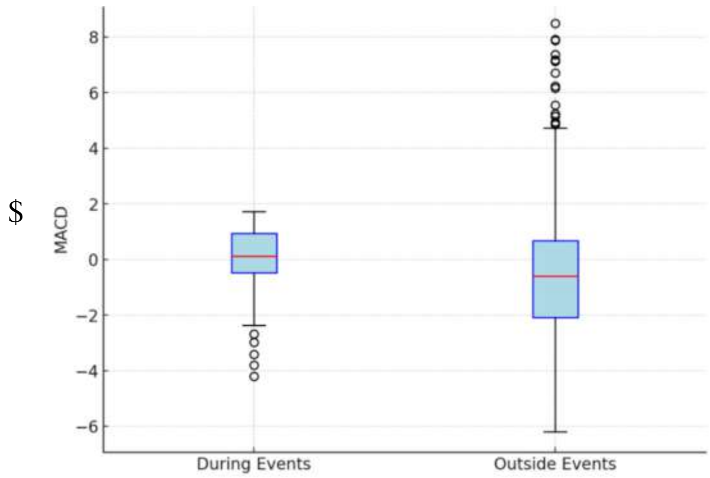
The correlation chart reveals significant relationships between the technical indicators studied, providing a solid basis for combining them in disciplined strategies:

- RSI_14 and Stochastic_%K: The positive correlation (0.72) shows a strong relationship between these two oscillators, indicating that they often move in the same direction. This interaction validates their complementarity in detecting overbought and oversold areas, particularly in periods of low volatility.
- RSI_14 and MACD: A moderate correlation (0.45) reflects that, although related, these indicators provide different perspectives. The RSI measures the relative strength of prices, while the MACD emphasizes the momentum of trends.
- Stochastic_%K and MACD: The relatively low correlation (0.32) indicates that these two indicators can capture distinct aspects of the market, making them valuable when used for clear and disciplined signals.

These results support theories about the effectiveness of indicator combinations in reducing behavioral biases, a point also validated by experts, who recommend the RSI for maintaining emotional discipline and the MACD for confirming trends.

Figure 5: Boxplot of the distribution of technical indicators during and outside of Covid-19





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Boxplots reveal a significant impact of geopolitical events on key technical indicators. During these periods, the SMA_50 and EMA_20 show sharply reduced and tighter values, confirming a loss of reliability in trends and a reduction in their amplitude. Outside of crises, these indicators show wider dispersion, reflecting an increased ability to capture market trends. The RSI_14, on the other hand, is significantly higher and more volatile during events, suggesting market overreaction and increased instability in overbought/oversold conditions. The MACD, a momentum indicator, shows greater dispersion outside of crises, while remaining more stable but less responsive during events, reducing its relevance for anticipating reversals. These results confirm that geopolitical events disrupt the reliability of trend indicators, requiring a more cautious approach and the integration of complementary analyses to limit decision-making errors.

Conclusion

This study highlights the structural fragility of technical indicators when confronted with highly unstable market environments, such as those generated by geopolitical crises. Through the analysis of several financial assets over a period that included both stable and turbulent phases (notably the Covid-19 crisis), it appears that technical tools, although robust in normal times, become partially ineffective, even counterproductive, in the context of exogenous shocks.

The results confirm a significant alteration in the internal consistency of the signals produced: moving averages become less sensitive to rapid reversals, oscillators display excessive volatility, and the MACD, a momentum indicator, neutralizes itself in chaotic price zones. These distortions reflect not only a technical limitation, but also an empirical translation of the behavioral mechanisms discussed in the behavioral finance literature (Kahneman & Tversky, 1979; Shiller, 2003), where panic, loss aversion, and herd behavior disrupt rational dynamics.

These observations confirm the criticisms levelled at purely technical analysis models, whose effectiveness relies on a certain continuity in market cycles (Murphy, 1999; Han, Yang & Zhou, 2016). When an exogenous shock breaks this continuity, indicators are no longer reliable prediction tools but become evidence of structural disorganization (Baker, Bloom & Davis, 2020). In times of crisis, the signals generated can thus be amplified or distorted by irrational collective behavior (Barberis et al., 1998), making it necessary to cross-reference technical, fundamental, and emotional market contexts.

In practice, these results invite us to re-examine the standardized use of technical indicators, particularly in environments of high uncertainty. It is becoming essential to adopt a contextualized reading of signals, to favor combinations of complementary indicators (RSI/MACD, Stochastic/SMA), and to integrate qualitative or fundamental variables to avoid biased decisions. Ultimately, the development of adaptive or hybrid models capable of adjusting to volatility regimes and exogenous events is a promising way to restore the robustness of technical analysis.

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