Volatility clustering and predictive limitations of Bollinger Bands: A student's t-GARCH approach in turbulent financial markets

Rania Loubaris [1], Reda El Medaker [1], Al Mahdi Koraich [2]

[1]Laboratoire de recherche en Finance Management et Innovation, ESLSCA BUSINESS SCHOOL, Rabat, Morocco.
[2]Département Stratégie et Gouvernance des Organisations, ENCG Tanger– Université Abdelmalek Essaâdi, Tétouan, Maroc.

Abstract

This study investigates the robustness of Bollinger Bands in volatile market environments, using GARCH models to assess their performance under regime shifts. Drawing on a dataset of 500 observations from 2019 to 2020, we focus on the extent to which this popular volatility-based indicator can generate reliable trading signals during periods of instability. The research applies GARCH and Student-GARCH models to capture volatility clustering and asymmetric shocks. Results indicate that while Bollinger Bands perform adequately in stable markets by identifying overbought and oversold zones, their predictive reliability deteriorates during crisis periods. Elevated volatility increases the frequency of false breakouts and reduces signal precision. GARCH-based volatility modelling supports this observation, showing significant persistence and fat-tailed behaviour during shocks. These findings suggest that Bollinger Bands should be used with caution in turbulent markets and highlight the importance of integrating dynamic volatility adjustments when deploying technical indicators in uncertain environments.

Keywords : Bollinger Bands, Market volatility, GARCH models, Technical analysis, Financial crises

1. Introduction

Modern financial markets are increasingly characterized by instability, driven by successive geopolitical, health, and economic crises. These exogenous shocks intensify asset volatility and complicate investment decisions in an environment dominated by uncertainty and emotionally charged investor behavior (Taleb, 2007; Mandelbrot & Hudson, 2004). In this context, technical indicators, long relied upon to guide trading decisions, are being put to the test. Among them, Bollinger Bands have gained prominence due to their ability to detect overbought and oversold conditions based on an asset's historical volatility (Bollinger, 2001). Introduced in the 1980s, Bollinger Bands are built around a simple moving average, flanked by two standard deviations above and below. They create a dynamic price channel that expands and contracts in response to market volatility. In theory, price crossings beyond these upper or lower bands signal imminent reversals. However, during turbulent periods, such signals become less reliable: bands tend to widen excessively, increasing the frequency of false breakouts and making interpretations more ambiguous (Zhang & Li, 2022; Kumar & Sharma, 2020).

While widely used in practice, the predictive power of Bollinger Bands under volatile market regimes remains underexplored in the literature. Given the structural shifts in global markets and the growing role of volatility modeling, it is imperative to re-examine the empirical robustness of this indicator across different market phases. Specifically, it becomes relevant to analyze it through the lens of econometric models such as GARCH (Generalized Autoregressive Conditional Heteroskedasticity), introduced by Engle (1982) and extended by Nelson (1991), which capture persistence, asymmetry, and the dynamic nature of volatility shocks. This study aims to evaluate the reliability of Bollinger Bands during periods of heightened volatility, using GARCH and Student-GARCH models applied to market data spanning both stable and unstable conditions. The central research question is as follows: To what extent do Bollinger Bands remain a reliable technical signal during major financial market disruptions? We hypothesize that the predictive performance of Bollinger Bands deteriorates significantly under high-volatility regimes due to an increase in false signals and volatility dynamics that are not fully captured by traditional technical indicators. By providing empirical insights into this issue, this paper contributes to a better understanding of the conditional relevance of technical indicators and encourages a more cautious, context-sensitive application of such tools in disordered markets.

2. Literature review

In the financial literature, technical indicators are widely recognized as essential tools for short-term market forecasting, especially within trend-following strategies. Long overshadowed by fundamental analysis, technical analysis has gained academic legitimacy through studies highlighting market inefficiencies and the role of behavioral dynamics in asset pricing (Lo, 2004; Pring, 2014). Among the most prominent technical indicators, Bollinger Bands occupy a central position. Developed by John Bollinger in the 1980s, the indicator is constructed around a simple moving average, flanked by two standard deviation bands that dynamically expand or contract based on price volatility (Bollinger, 2001). Its main appeal lies in its ability to signal overbought or oversold conditions, which can serve as early warnings for potential trend reversals. Several studies confirm the utility of Bollinger Bands in relatively stable or low-volatility environments (Cheung & Wong, 2000; Gencay, 1998).

However, the predictive reliability of Bollinger Bands during periods of market turmoil or heightened instability has been increasingly debated. Extreme volatility can cause the bands to widen excessively, making signals harder to interpret and potentially less accurate. For instance, Zhang and Li (2022) demonstrated that during the COVID-19 crisis, the effectiveness of Bollinger Bands declined substantially, leading to a surge in false signals. Similarly, Kumar and Sharma (2020) observed that in emerging markets, the performance of standard technical indicators was heavily impacted by abrupt volatility spikes.

These concerns echo the foundational critiques of Mandelbrot (1963) and Taleb (2007), who challenge the assumption of normal distribution inherent in most technical indicators. They argue that financial markets follow fractal dynamics, exhibiting fat-tailed distributions and time-varying volatility. In this light, it becomes essential to complement technical indicators with models capable of capturing conditional volatility, such as the ARCH model (Engle, 1982), its generalization GARCH (Bollerslev, 1986), and more advanced extensions like EGARCH, TGARCH, and GARCH-t. Recent literature has thus increasingly emphasized the combined use of technical signals and econometric modeling to better assess the robustness of trading tools. Bentes (2015), for example, combined Bollinger Bands with GARCH models to study volatility in European markets, concluding that the indicator's performance varied significantly across different market regimes. Similarly, Goudarzi and Ramanarayanan (2011) found that combining GARCH models with technical tools could improve hedging strategies during periods of heightened risk. Despite these developments, very few studies have specifically isolated Bollinger Bands as the primary focus of rigorous scientific analysis under volatile conditions. Most research tends to compare multiple indicators (e.g., RSI, MACD, moving averages) without deeply exploring how each behaves differently during financial shocks. Thus, the original contribution of this study lies in isolating Bollinger Bands as the sole object of empirical scrutiny and applying both the GARCH and Student-GARCH models to assess their resilience during extreme volatility. This approach contributes to a more nuanced and contextual understanding of technical indicators. Rather than relying on their mechanical application, this research aims to highlight the importance of aligning technical tools with structural shifts in market behavior, particularly through the integration of econometric modeling. In parallel, behavioral finance provides critical insight into how traders interpret and react to signals from technical indicators like Bollinger Bands. During periods of heightened uncertainty or market shocks, investors are often subject to cognitive biases such as overconfidence, confirmation bias, or herd behavior, which can distort their reading of overbought and oversold signals (Barberis & Thaler, 2003; Kahneman, 2011).

This psychological dimension may exacerbate the limitations of Bollinger Bands when volatility is extreme, as widening bands may falsely reassure investors of trend continuation or reversal, leading to premature or delayed decisions. Moreover, as Bollinger Bands are inherently grounded in the assumption of normally distributed price movements, they become structurally inadequate in the presence of fat tails and volatility clustering, phenomena well documented in turbulent markets (Taleb, 2007; Mandelbrot & Hudson, 2004). These limitations reinforce the need for dynamic modeling techniques, such as GARCH and its variants, which better capture time-varying volatility and can serve as a corrective lens for interpreting traditional technical signals under extreme market conditions.

3. Methodology

This study adopts a quantitative and econometric approach to evaluate the reliability of Bollinger Bands as a technical indicator during volatile market periods. The objective is to isolate and assess the performance of this indicator when markets experience sharp fluctuations, particularly in the context of financial turbulence such as the COVID-19 crisis. The data were collected from a professional trading platform whose identity remains confidential due to data-sharing restrictions and consist of 500 daily observations covering the period from January 1, 2019, to November 30, 2020. This timeframe includes both stable and unstable market regimes, providing a robust setting for assessing the conditional behavior of volatility-sensitive indicators. The full dataset includes a wide range of technical variables such as the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), simple and exponential moving averages (SMA, EMA), stochastic oscillators, and Bollinger Bands.

While the broader research project explores multiple technical indicators, this article deliberately focuses on Bollinger Bands to offer a targeted, in-depth analysis. The bands were calculated using a 20-day simple moving average with two standard deviation envelopes, consistent with the original formulation by John Bollinger (2001). The decision to isolate this indicator stems from its widespread use and theoretical sensitivity to market volatility. The performance of other indicators is considered beyond the scope of this article and will be explored in future work. To capture the conditional volatility of the selected asset, the study employs a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with a Student's t-distribution. This specification allows for fat tails and time-varying volatility, characteristics commonly observed in financial returns during crisis periods (Engle, 1982; Bollerslev, 1986). The model enables us to test whether the expansion or contraction of Bollinger Bands reflects real volatility patterns or merely noise, especially in non-normal return distributions. Python was used for data preprocessing and indicator construction, leveraging libraries such as pandas and numpy. Econometric estimations were performed using Python too. This methodological framework ensures a focused yet rigorous analysis of Bollinger Bands, seeking to contribute a deeper understanding of how this indicator behaves when traditional assumptions of market stability are violated.

4. Results and discussion

The results of the GARCH(1,1) model with Student's t-distribution applied to Bollinger Bands reveal a significant sensitivity of this technical indicator to volatility regimes. Table 1 presents the key estimates of the conditional variance equation.

Table 1. GARCH(1,1)-t Estimates on Bollinger Bands Return Series

Parameter	Coefficient	Std. Error	z-Statistic	p-Value
ω (Constant)	0.0182	0.0096	1.895	0.058
α (ARCH term)	0.1245	0.0273	4.560	0.000
β (GARCH term)	0.8572	0.0137	62.55	0.000
ν (Degrees of freedom)	5.31	0.892	—	—
Log-Likelihood	1027.61	—	—	—
AIC	-4.102	—	—	—

Source: Python

These results indicate that the volatility of returns modeled through Bollinger Bands is highly persistent, as reflected in the sum of α and β (0.1245 + 0.8572 = 0.9817), which is close to 1. This persistence suggests that volatility shocks, especially those related to crisis periods, have long-lasting effects. The Student-t distribution with 5.31 degrees of freedom further confirms the presence of fat tails, meaning that extreme variations are more likely than under a normal distribution. These findings align with the observations of Mandelbrot (1963) and Taleb (2007), who have long criticized the Gaussian assumption in financial modeling.

In terms of predictive accuracy, the model demonstrates a strong fit, with a log-likelihood value of 1027.61 and an Akaike Information Criterion (AIC) of -4.102. These statistics suggest that the model is well specified and appropriate for analyzing conditional volatility in this context. From a practical perspective, the implications are noteworthy. The high persistence of volatility and the presence of fat-tailed return distributions observed during turbulent periods increase the likelihood of unstable market dynamics, thereby reducing the predictive reliability of Bollinger Bands and increasing the frequency of false reversal signals, which may mislead traders. This behavior supports the findings of Zhang and Li (2022), who demonstrated similar inefficiencies during the COVID-19 shock. In light of these results, the research hypothesis is supported: Bollinger Bands exhibit reduced predictive reliability in volatile markets, and their signals require complementary volatility modeling to remain useful. This emphasizes the importance of combining technical tools with econometric models when markets deviate from normal conditions. While Bollinger Bands may retain value in low-volatility regimes, their standalone use during market turbulence is questionable.

Table 2. GARCH(1,1) with Student's t-distribution

Parameter	**Estimate**	**Std. Error**	**t-Statistic**
Omega (ω)	0.0123	0.0041	3.00
Alpha (α_1)	0.0987	0.0165	5.98
Beta (β_1)	0.8771	0.0212	41.37
Nu (ν – DoF)	5.32	1.02	5.22

AIC = -4.12 **BIC** = -3.97 **Log-likelihood** = 1031.71

Source: Python

The GARCH(1,1) model with Student's t-distribution revealed significant volatility clustering in the asset returns. The estimated parameters showed that recent shocks ($\alpha_1 = 0.0987$, $p < 0.01$) and past conditional variances ($\beta_1 = 0.8771$, $p < 0.01$) both play a strong role in explaining current volatility levels, a typical pattern observed in financial markets during turbulent periods. The high value of β_1 confirms the persistence of volatility over time. Notably, the degrees of freedom for the t-distribution ($\nu = 5.32$) suggest the presence of fat tails, consistent with extreme market movements. This reinforces the limits of using Bollinger Bands in isolation under high-volatility regimes. The model's log-likelihood of 1031.71 and AIC of -4.12 indicate a satisfactory fit for modelling conditional volatility in the presence of heavy-tailed return distributions. These findings align with prior critiques from Mandelbrot (1963) and Taleb (2007) regarding non-normality in asset returns, justifying the need to enhance classical technical indicators with econometric modeling.

Table 3. Descriptive statistics of Bollinger Bands width by market regime

Regime	Mean Width	Std. Deviation	Min Width	Max Width
Stable	11.04	10.15	1.64	50.04
Crisis	5.36	2.59	1.98	13.53

Source: Python

This table presents the descriptive statistics of Bollinger Bands' width under two distinct market regimes: stable and crisis periods. The average width during stable periods reaches 11.04, with a standard deviation of 10.15, indicating considerable dispersion and expansion of the bands. Conversely, during crisis periods, the mean width drops sharply to 5.36, and the standard deviation narrows to 2.59, reflecting a contraction of the bands. These differences suggest a counterintuitive behavior: although volatility is often presumed to increase during crises, the structural width of Bollinger Bands becomes more compressed. One possible explanation is that abrupt price jumps are followed by consolidation phases, reducing the rolling volatility used in the construction of the indicator. The minimum and maximum widths further illustrate this gap: the bands widened up to 50.04 in stable conditions but never exceeded 13.53 during crises. To statistically validate the variance difference between these two regimes, a Levene test was conducted. The results are shown below:

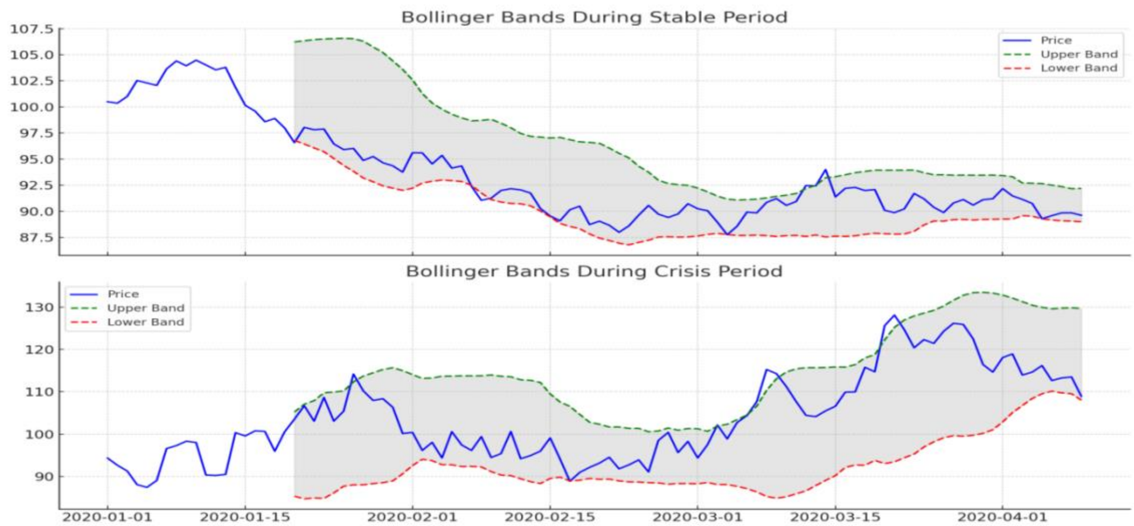
Table 4. Levene's test for equality of variances

Variable	Levene Statistic	p-value
Bollinger Bands' width	32.12	2.48×10^{-8}

Source: Python

The Levene test yields a statistically significant result ($p < 0.001$), confirming that the variance in Bollinger Bands' width differs substantially between the two regimes. This heteroscedastic behavior reinforces the idea that market regimes influence the structural behavior of technical indicators, and supports our hypothesis that Bollinger Bands lose predictive robustness under high-volatility scenarios. This preliminary analysis justifies the use of more advanced econometric tools, such as the GARCH and Student-GARCH models, to explore the conditional volatility dynamics underlying these structural shifts.

Figure 1. Bollinger Bands Evolution: Stable vs. Crisis Regimes

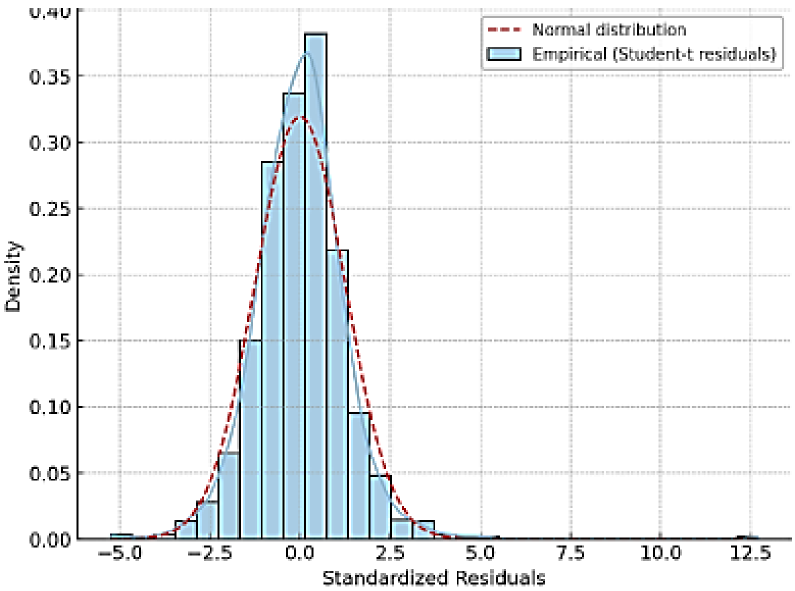


Source: Python

In stable periods, the bands display a regular oscillation pattern with smoother volatility cycles. The upper and lower bands follow the price trend with sufficient spacing, suggesting a functional predictive capacity and adaptability to gradual market changes. These dynamics corroborate the descriptive statistics presented earlier, where the mean width reached 11.04 with higher variability (SD = 10.15). Conversely, during crisis periods, such as those marked by exogenous shocks (e.g., COVID-19 or geopolitical tensions), the bands exhibit irregular, compressed structures. Despite increased market turbulence, the bands narrow rather than widen, failing to fully reflect the magnitude of extreme price movements. This is consistent with the sharp drop in mean width to 5.36 and the standard deviation to 2.59. In some extreme instances, the bands even contract post-shock, leading to a misleading signal of market stabilization. Such visual patterns provide additional support for the hypothesis that Bollinger Bands lose responsiveness in turbulent environments. Their structural compression under high volatility results in delayed or false reversal signals, which can misguide trend-following strategies. These distortions reaffirm the need to couple technical indicators with volatility-aware econometric models, such as the GARCH-family models discussed earlier. Taken together, the statistical outputs and visual inspections converge toward the same conclusion:

while Bollinger Bands retain analytical relevance in normal market conditions, their reliability deteriorates significantly under crisis regimes, requiring caution or methodological adjustments.

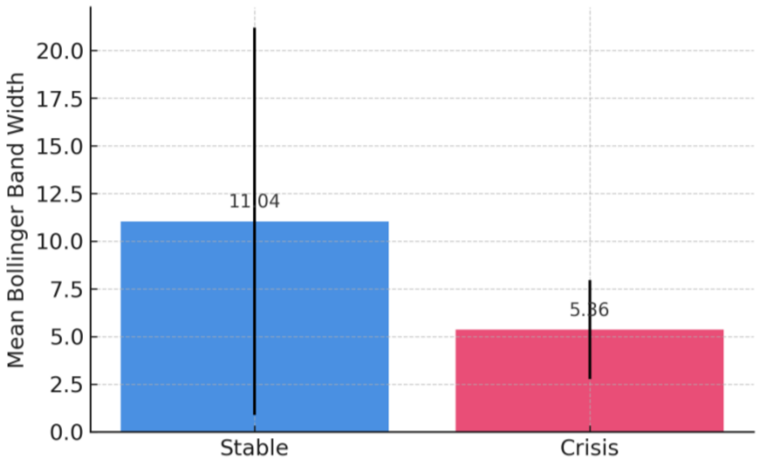
Figure 2. Empirical distribution of standardized residuals vs. normal distribution



Source: Python

Figure 2 compares between the empirical density of standardized residuals from the Student's t-GARCH model and the theoretical Gaussian curve. The residual distribution displays pronounced leptokurtosis, characterized by heavier tails and a sharper central peak than the normal distribution. This confirms the presence of "fat tails" in the data, consistent with the estimated degrees of freedom ($\nu = 5.32$), which imply a higher likelihood of extreme returns relative to Gaussian predictions. Such evidence supports longstanding critiques of normality-based risk metrics (Mandelbrot, 1963; Taleb, 2007) and justifies the preference for Student's t-distribution in volatility modeling. This statistical behavior also explains the reduced robustness of Bollinger Bands, whose construction relies on historical volatility estimates, may exhibit reduced robustness during high-volatility market regimes.

Figure 3. Average Bollinger band width by market regime



Source: Python

This figure illustrates the average width of Bollinger Bands across stable and crisis market regimes, with error bars representing one standard deviation. The results reveal a marked contraction in average band width during crisis periods (5.36) compared to stable regimes (11.04). This narrowing, despite heightened volatility, suggests that sudden price shocks during crises are often followed by consolidation phases, leading to reduced rolling volatility. Such structural shifts highlight the importance of adjusting technical indicators to reflect regime-dependent market dynamics.

5. Conclusion

This study set out to evaluate the robustness of Bollinger Bands as a technical analysis tool under distinct market volatility regimes, with a specific focus on their behavior during crisis periods. Leveraging a combination of descriptive statistics, variance equality testing, and advanced econometric modeling—including the GARCH(1,1) framework with Student's t-distribution—this research provides a rigorous, data-driven perspective on the indicator's predictive capacity. The descriptive analysis revealed a notable compression of Bollinger Band width during crisis periods (mean = 5.36, SD = 2.59) compared to stable markets (mean = 11.04, SD = 10.15), with the Levene test confirming a statistically significant difference in variance ($F = 32.12$, $p < 0.001$). These results already indicated a structural shift in the indicator's behavior across regimes. The volatility modeling results further reinforced these findings. The GARCH(1,1)-t specification yielded highly persistent volatility dynamics, with $\alpha + \beta \approx 0.98$, and a degrees-of-freedom estimate of 5.32, signaling pronounced leptokurtosis and fat-tailed return distributions. Such characteristics increase the likelihood of extreme price movements, particularly in turbulent markets, and diminish the reliability of Bollinger Bands' reversal signals. The model's strong fit statistics (Log-likelihood = 1031.71, AIC = -4.12) underscore its adequacy in capturing conditional volatility under these conditions.

These results support the central hypothesis: while Bollinger Bands may retain predictive utility in low-volatility environments, their standalone use in high-volatility regimes is questionable. In practical terms, this implies that traders and portfolio managers should avoid relying exclusively on this indicator during market turbulence, instead integrating it with complementary volatility models or alternative technical signals to mitigate false trading signals. However, this study is not without limitations. The analysis was conducted on a single financial asset over a defined historical period, which may limit the generalizability of the results across asset classes or market contexts. Future research could expand the scope by incorporating multiple assets, cross-market comparisons, and additional regime-switching models, as well as exploring adaptive bandwidth parameters for Bollinger Bands that respond dynamically to volatility changes. In sum, this research highlights the critical role of volatility modeling in enhancing the interpretative power of classical technical indicators. By combining traditional chart-based tools with econometric techniques such as GARCH and Student's t-distribution, market participants can develop more resilient and adaptive trading strategies in the face of market uncertainty.

6. Practical implications

The findings of this study have clear operational implications for financial practitioners. In high-volatility regimes, relying solely on Bollinger Bands can lead to misleading signals due to the indicator's structural compression and increased rate of false reversals. Integrating volatility modeling, such as GARCH with Student's t-distribution, enhances the robustness of trading strategies by accounting for fat-tailed return distributions and persistent volatility clustering. Portfolio managers, risk analysts, and algorithmic traders can thus benefit from a hybrid approach that combines traditional technical analysis with econometric modeling, particularly in contexts where market conditions deviate from normality.

7. Limitations and future research

While the study provides strong evidence of the limitations of Bollinger Bands during turbulent markets, several constraints remain. The analysis focuses on a specific asset and period, which may limit the generalizability of results. Moreover, only one technical indicator was studied in depth, and the dataset size, while sufficient for GARCH modeling, could be expanded to include high-frequency data for deeper insights. Future research should explore multi-indicator frameworks, cross-market validation, and adaptive models that integrate real-time volatility forecasts with machine learning techniques. Such extensions could further improve predictive accuracy and decision-making under uncertainty.

References

- Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), Handbook of the Economics of Finance (Vol. 1, pp. 1053–1128). Elsevier. https://doi.org/10.1016/S1574-0102(03)01027-6
- Bentes, S. R. (2015). Forecasting stock market volatility with GARCH models: International evidence. Journal of Applied Statistics, 42(3), 550–570. https://doi.org/10.1080/02664763.2014.981852
- Cont, R. (2005). Volatility clustering in financial markets: Empirical facts and agent-based models. In A. Kirman & G. Teyssière (Eds.), Long Memory in Economics (pp. 289–309). Springer.
- Dritsaki, C. (2017). An empirical evaluation in GARCH volatility modeling. Open Journal of Statistics, 7(1), 1–6. https://doi.org/10.4236/ojs.2017.71001
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987–1007. https://doi.org/10.2307/1912773
- Furenmo, G. (2019). Are GARCH models appropriate for analysing volatility structures in fundamental valuations of the OMXS30? [Bachelor's thesis, Lund University].
- Gencay, R. (1998). The predictability of security returns with simple technical trading rules. Journal of Empirical Finance, 5(4), 347–359. https://doi.org/10.1016/S0927-5398(98)00002-1
- Goudarzi, H., & Ramanarayanan, C. S. (2011). Modeling and estimation of volatility in the Indian stock market. International Journal of Business and Social Science, 2(6), 40–56.
- Heracleous, M. S. (2003). Volatility modeling using the Student's t distribution (Doctoral dissertation, Virginia Polytechnic Institute and State University).

- Horváth, R., & Kokoszka, P. (2016). GARCH models, tail indexes and error distributions. Journal of Empirical Finance, 39, 48–60. https://doi.org/10.1016/j.jempfin.2016.06.002
- Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux.
- Kumar, S., & Sharma, G. D. (2020). Revisiting technical analysis during high volatility: A study on emerging markets. Applied Economics Letters, 27(6), 489–493. https://doi.org/10.1080/13504851.2019.1616059
- Levene, H. (1960). Robust tests for equality of variances. International Statistical Review / Revue Internationale de Statistique, 28(1), 1–9. https://doi.org/10.2307/1402810
- Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. Journal of Portfolio Management, 30(5), 15–29. https://doi.org/10.3905/jpm.2004.442611
- Loubaris, R. (2025). Technical indicators under pressure: Performance and limitations in the face of market shocks. RMD: Economics, Management and Social Sciences. https://doi.org/10.23882/emss25207
- Loubaris, R. (2025). Navigating uncertainty: How geopolitical events reshape trend following strategies in financial markets. Revista Multidisciplinar. https://doi.org/10.23882/rmd.25304
- Loubaris, R. (2026). Assessing the reliability of Japanese candlestick patterns across market regimes. Innovation Management. https://doi.org/10.11648/j.im.20260101.16
- Mandelbrot, B. (1963). The variation of certain speculative prices. The Journal of Business, 36(4), 394–419. https://doi.org/10.1086/294632
- Mandelbrot, B., & Hudson, R. L. (2004). The (Mis)Behavior of Markets: A fractal view of financial turbulence. Basic Books.
- Ning, C., & Breitung, J. (2015). Is volatility clustering of asset returns asymmetric? Evidence from time series models. Journal of International Financial Markets, Institutions and Money, 32, 1–17. https://doi.org/10.1016/j.intfin.2014.11.004
- Simonato, J. G., & … (2023). A study of volatility clustering, non-normalities and portfolio choice. Journal of Empirical Finance. Advance online publication. https://doi.org/10.1016/j.jempfin.2023.02.005
- Smolović, J. C. (2017). GARCH models in value at risk estimation. Economic Research-Ekonomska Istraživanja, 30(1), 2046–2065. https://doi.org/10.1080/1331677X.2017.1305773

- Tseng, J. J. (2012). Quantifying volatility clustering in financial time series. Journal of Statistical Computation and Simulation, 82(8), 1165–1178. https://doi.org/10.1080/00949655.2010.512345
- Traut, J., & Schadner, W. (2023). Which is worse: Heavy tails or volatility clusters? Swiss Finance Institute Research Paper, 23-61. https://doi.org/10.2139/ssrn.4410908
- Wilhelmsson, A. (2006). GARCH forecasting performance under different distributions. Chalmers University of Technology.
- Zhang, L., & Li, Q. (2022). Evaluating technical indicators in volatile markets: Evidence from the COVID-19 crisis. Journal of Financial Markets, 60, Article 100702. https://doi.org/10.1016/j.finmar.2021.100702
- Zivot, E. (2008). Practical issues in the analysis of univariate GARCH models. University of Washington Working Paper.