Structural Breaks as Investment Signals: BFAST vs. CUSUM in Quito's Stock Market During COVID-19 Pandemic

Carolina Quintero, Alexander Andrade, and Erith Muñoz

***Abstract*—This study investigates the potential of structural break detection in stock price time series as a tool for investment decision-making in emerging markets. Operating under the hypothesis that structural breaks reflect shifts in underlying price trends, we conduct an empirical analysis of investment performance in the Quito Stock Exchange (QSE) using monthly average prices from 2013 to 2022 for the ten most actively traded companies, selected for their transaction volume and sectoral representativeness. Importantly, this period coincided with the COVID-19 pandemic, providing a natural context to explore how structural breaks behave under heightened market volatility. Two algorithms—CUSUM and BFAST—are applied and compared in terms of their ability to identify actionable breakpoints and generate profitable buy/sell signals. Results show that BFAST, originally developed for remote sensing applications, consistently outperforms CUSUM: it detects a higher proportion of successful signals, yields stronger average returns over a six-month evaluation window (+17% in the financial sector and +18.75% in the productive/commercial sector), and achieves superior risk-adjusted performance as measured by Sharpe ratios. Statistical validation using the Wilcoxon signed-rank test confirms the significance of BFAST's advantage (p = 0.005). Taken together, these findings position BFAST as a robust and economically relevant tool for financial time-series analysis, extending its utility beyond traditional domains and offering investors a methodologically sound framework for decision-making in volatile market environments.**

Link to graphical and video abstracts, and to code:
https://latamt.ieeer9.org/index.php/transactions/article/view/10113

***Index Terms*—BFAST Algorithm, CUSUM Test, Structural Break Detection, Investment Strategy, Time Series Analysis, Pandemic, COVID-19 Impact.**

I. Introduction

THE COVID-19 pandemic disrupted financial markets globally, with particularly acute effects in Latin America [1]–[7]. Like many national exchanges, the Quito Stock Exchange (QSE) experienced notable volatility, shaped by pandemic-induced economic contraction and international market pressures [8]–[10]. Ecuador's dollar-based economy makes it uniquely sensitive to external shocks, emphasizing the need for localized and methodologically robust analysis [11].

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The Ecuadorian stock market includes transactions from both the Guayaquil Stock Exchange (GSE) and the Quito Stock Exchange (QSE), collectively represented by the Ecuador Stock Index (ECUINDEX) [11]. Previous studies, such as [12], have examined pandemic impacts qualitatively, reporting that 66% of companies faced negative outcomes due to reduced economic activity. Quantitative evidence from the Central Bank of Ecuador further highlights the severity of the shock: the QSE accounted for 69% of national exchange activity in 2019, but by December 2020 this share had fallen to 40%, consistent with a 66% decline in overall trading volume [13].

Building on this context, the present study shifts focus from describing pandemic impacts to evaluating the utility of structural break detection as a decision-making tool for investors. Specifically, we apply the Breaks For Additive Season and Trend (BFAST) algorithm—originally developed for remote sensing applications—to financial time series, comparing its performance with the classical CUSUM approach. BFAST's ability to isolate trend shifts and seasonal components offers a promising framework for identifying actionable signals in volatile markets [14].

Rather than treating breakpoints as descriptive markers of crisis, we assess whether detected breaks correspond to profitable buy or sell opportunities. Breaks are analyzed across three temporal phases: (i) PRECOVID (2019), (ii) COVID (2020), and (iii) POSTCOVID (2021–2022). For each breakpoint, we evaluate six-month investment performance, validated through Wilcoxon signed-rank tests and Sharpe ratios. This approach reframes structural break detection from a diagnostic tool into a strategic mechanism for investment timing, providing both statistical rigor and economic relevance in the comparison of BFAST and CUSUM.

This study contributes to the literature by introducing BFAST as a novel tool for financial break detection, systematically comparing its performance with CUSUM, and validating investment signals through both statistical (Wilcoxon signed-rank test) and economic (Sharpe ratio) measures. In doing so, it bridges methodological rigor with practical relevance, offering a framework for investors to transform structural break analysis into actionable decision-making in emerging markets.

II. Theoretical Framework

Structural break analysis is widely used to understand volatility in financial markets [15]–[17]. Among the most established approaches is the cumulative sum (CUSUM) test [18], originally developed by [19] and later extended through F-statistic based methods [20], [21] and generalized fluctuation tests [22]. These approaches provide robust tools for identifying deviations in time series, though they typically focus on single structural components.

Building on this tradition, iterative econometric models have sought to disaggregate time series into trend, seasonality, and irregular components [23]. Within this framework, structural breaks are identified as changes in slope or intercept of the trend component, while seasonal fluctuations are modeled separately. This decomposition underpins more advanced algorithms such as MOSUM [24] and BFAST [25].

BFAST represents a conceptual enhancement of MOSUM, integrating three modules: (i) breakpoint detection, (ii) seasonality decomposition, and (iii) trend estimation. Its iterative refinement process distinguishes short-term noise from persistent structural changes, improving precision relative to methods that rely solely on breakpoint identification [26]. While BFAST has been widely applied in remote sensing—e.g., forest monitoring and land cover change [27], [28]—its application to financial time series remains unexplored. This study therefore evaluates the potential of BFAST to detect structural breaks in stock prices, comparing its performance with the classical CUSUM test.

To clarify the conceptual differences between the two approaches, Fig. 1 presents a schematic comparison of CUSUM and BFAST. While CUSUM focuses solely on detecting breakpoints based on cumulative deviations, BFAST integrates trend estimation, seasonality decomposition, and breakpoint detection into a unified framework. This modular structure allows BFAST to iteratively refine its results, distinguishing persistent structural changes from short-term noise.

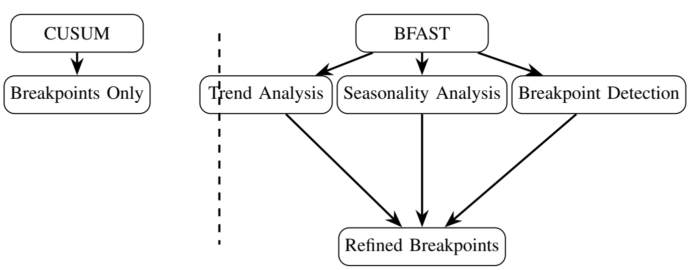


Fig. 1. Conceptual comparison of CUSUM and BFAST approaches. CUSUM detects breakpoints via cumulative deviations, while BFAST integrates trend, seasonality, and breakpoint modules for refined structural change detection.

A. CUSUM Test

The CUSUM (Cumulative Sum) test is based on monitoring the cumulative sum of deviations from the mean. For a time series $\{y_t\}$ with mean μ, the CUSUM statistic is defined as [29]:

$$S_t = \sum_{i=1}^{t} (y_i - \mu), \quad t = 1, 2, \ldots, T \tag{1}$$

A structural break is indicated when S_t crosses predefined confidence boundaries. In practice, the standardized CUSUM statistic is often used:

$$C_t = \frac{1}{\hat{\sigma}} \sum_{i=1}^{t} (y_i - \hat{\mu}) \tag{2}$$

where $\hat{\mu}$ and $\hat{\sigma}$ are the sample mean and standard deviation. Breakpoints are detected when C_t exceeds critical values derived from asymptotic distributions.

B. BFAST Algorithm

BFAST (Breaks For Additive Seasonal and Trend) decomposes a time series into trend, seasonal, and remainder components [25]:

$$y_t = T_t + S_t + e_t \tag{3}$$

where T_t is the trend, S_t is the seasonal component, and e_t is the remainder. Structural breaks are detected by iteratively applying regression models to the trend and seasonal components. The trend component is modeled as:

$$T_t = \beta_0 + \beta_1 t + \sum_{j=1}^{m} \gamma_j D_{j,t} + \varepsilon_t \tag{4}$$

where $D_{j,t}$ are dummy variables indicating potential breakpoints, and γ_j captures the magnitude of the break. Breaks are identified when coefficients γ_j are statistically significant.

III. Methodology

A. Data Source

This study utilizes monthly time-series data on stock prices from companies listed on the Quito Stock Exchange (QSE), covering the period from January 2013 to December 2022. Observations from 2013 to 2018 were used to calibrate structural break detection algorithms, while the period from 2020 to 2022 was designated for breakpoint identification and signal evaluation. The year 2019 serves as a transitional benchmark and is labeled as the PRE-COVID phase, followed by the COVID phase (2020) and the POST-COVID phase (2021–2022).

B. Company Selection and Data Processing

During the study period, only 25 companies recorded transactions in the QSE. On average, the exchange registered 30.5 transactions per month, equivalent to roughly one transaction per day across all listed firms. This low trading frequency limits the feasibility of daily-level analysis and necessitates a monthly aggregation approach.

Given the sparse data, monthly average stock prices (MASP) were computed for each company. To ensure representativity and analytical robustness, the ten companies with the highest number of months containing transactions were selected. Table I summarizes these firms, including their listing dates, total months with recorded quotes, and the extent of missing data. Collectively, these ten companies account for 76.6% of all QSE transactions during the study period.

TABLE I
COMPANIES SELECTED FOR ANALYSIS

Company	Quotes	Start Date	Missing Quotes
Corporación Favorita	120	01/Jan/2013	0/120
Banco Guayaquil	119	01/Jan/2013	1/120
Holcim Ecuador	112	01/Jan/2013	12/120
Banco Pichincha	106	01/Jan/2013	14/120
Produbanco	93	01/Jan/2013	27/120
Cervecería Nacional	86	01/Mar/2015	12/84
San Carlos	77	01/Jan/2013	48/120
BVQ	55	01/Feb/2018	9/57
Industrias Ales	54	01/Jan/2013	71/120
Mutualista Pichincha	53	01/Jan/2017	12/72

To address missing values, a last-observation-carried-forward (LOCF) imputation method was applied to each MASP series. This ensured continuity and preserved the temporal structure required for structural break detection. The resulting dataset enabled the implementation of both the CUSUM test and the BFAST algorithm, facilitating a comparative evaluation of their performance in generating investment signals.

C. Structural Break Detection

The primary objective of this study is to assess the ability of structural break detection algorithms to identify trend shifts that can inform stock buying and selling decisions. Breakpoint detection was applied to the MASP series of each selected company across the PRE-COVID, COVID, and POST-COVID phases.

Both the CUSUM test and the BFAST algorithm were implemented in R, using the `strucchange` [30] and `bfast` [31] packages, respectively. The analysis focused on identifying breakpoints associated with directional changes in trend, which were then interpreted as potential investment signals.

D. Investment Signal Generation

Detected breakpoints were classified as investment signals based on the direction of the trend shift. A downward break was treated as a simulated buy signal, anticipating price recovery, while an upward break was interpreted as a sell signal, anticipating price decline. This framing allows structural breaks to serve as proxies for decision-making under volatile market conditions, such as those observed during the COVID-19 pandemic.

E. Performance Evaluation

To validate the effectiveness of BFAST and CUSUM in generating actionable signals, two complementary evaluation metrics were employed. First, the Wilcoxon signed-rank test [32] was applied to paired returns to assess whether BFAST systematically outperformed CUSUM. This non-parametric test is appropriate given the small sample sizes and non-normal distribution of returns.

Second, Sharpe ratios [33] were computed to evaluate risk-adjusted performance, capturing the trade-off between mean returns and volatility. Sharpe Ratios were calculated according to the standard formula $SR = (R_p - R_f/\sigma_p)$, where R_p is the mean return of the detected signals, R_f is the risk-free rate, and σ_p is the standard deviation of returns. In this study, the risk-free rate was set to 0, consistent with prior applications in low-liquidity emerging markets. Negative Sharpe Ratios are reported directly without adjustment, reflecting cases where the algorithm generated returns below the risk-free benchmark.

Both metrics were calculated at the company level to account for firm-specific heterogeneity, and at the global level to assess aggregate robustness. This dual validation framework ensures that both statistical significance and economic relevance are considered in comparing the two approaches.

IV. RESULTS AND ANALYSIS

This section presents the key results from the detection and evaluation of structural breaks in stock prices between January 2019 and December 2022, using the BFAST and CUSUM algorithms. Figs. 2 and 3 illustrate the breakpoints identified for companies in the financial sector and in the productive and commercial sector, respectively. In each figure, the left panels display the outcomes of BFAST, while the right panels show the corresponding results from CUSUM.

For clarity, the study period is divided into three phases: PRE-COVID (2019, shown in yellow), COVID (2020, shown in red), and POST-COVID (2021–2022, shown in blue). The y-axis represents monthly average share prices in US dollars, while the x-axis denotes time in years. Vertical lines mark the structural breaks detected, with blue lines indicating positive breaks (associated with price increases) and red lines indicating negative breaks (associated with price decreases).

While the figures provide a visual overview of breakpoints, the analysis extends beyond graphical inspection. To assess the reliability and economic relevance of the detected signals, performance was validated at both the company and global levels. Specifically, Wilcoxon signed-rank tests were applied to paired returns to evaluate statistical significance, offering a robust non-parametric measure suitable for small samples and non-normal distributions. In parallel, Sharpe ratios were computed to assess risk-adjusted performance, capturing the trade-off between mean returns and volatility. This dual evaluation framework ensures that the results are not only statistically robust but also economically meaningful, providing a solid basis for comparing BFAST and CUSUM in subsequent subsections.

A. Algorithm Parametrization

The performance of structural break detection methods depends critically on the choice of parameters. To ensure comparability and replicability, we explicitly describe the parametrization used for both CUSUM and BFAST in this study.

1) CUSUM: The CUSUM test was implemented using standardized cumulative sums of residuals. The key parameters are:

- Reference mean ($\hat{\mu}$): estimated from the pre-break sample.
- Standard deviation ($\hat{\sigma}$): computed from residuals to normalize deviations.

- Confidence boundaries: set at the 95% level, so that breaks are flagged when the cumulative sum statistic exceeds critical values.

This parametrization ensures sensitivity to moderate deviations while controlling for false positives.

2) BFAST: BFAST decomposes the time series into trend, seasonal, and remainder components. The main parameters are:

- Seasonal component (S_t): modeled with a harmonic term of period 12 to capture annual seasonality in monthly data.
- Trend component (T_t): estimated via piecewise linear regression, with breakpoints selected using the Bayesian Information Criterion (BIC).
- Iteration scheme: the algorithm iteratively fits and tests for breaks until no further statistically significant breakpoints are detected.

This parametrization allows BFAST to capture both abrupt shocks and gradual trend shifts, making it particularly suitable for periods of heightened volatility such as the COVID-19 pandemic.

3) Validation: To evaluate the economic relevance of detected breaks, investment signals were generated at each breakpoint and validated using:

- Six-month investment windows to assess profitability.
- Wilcoxon signed-rank tests to confirm statistical significance of differences between BFAST and CUSUM returns.
- Sharpe ratios to measure risk-adjusted performance.

This parametrization framework ensures that both algorithms are applied consistently, with breakpoints selected in a statistically rigorous manner and validated through economic performance metrics.

B. Structural Breaks Detection

Across the PRE-COVID, COVID, and POST-COVID phases, both BFAST and CUSUM identified structural breaks in the financial and productive–commercial sectors, though with differences in timing and interpretability. In the PRE-COVID phase, detected breaks were relatively infrequent and generally reflected gradual adjustments rather than sharp disruptions, consistent with the more stable market conditions of 2019. During the COVID phase, breaks were more pronounced, particularly in the financial sector where temporary declines were followed by recovery signals, and in the productive–commercial sector where heterogeneity was observed.

In the POST-COVID phase, both sectors exhibited renewed break activity associated with recovery and adjustment, though BFAST captured these shifts more consistently and in closer alignment with observed market volatility, whereas CUSUM often produced earlier or less conclusive signals. Overall, the detection patterns highlight that BFAST provided more coherent and economically relevant break identification across all phases, while CUSUM's signals were less stable across firms and periods. These temporal and sectoral patterns set the stage for the statistical validation presented in the next subsection, where Wilcoxon tests and Sharpe ratios are used to assess the robustness and economic relevance of the detected signals.

C. Signal Investment Performance

Table II reports the company-level comparison of BFAST and CUSUM in terms of mean returns, Sharpe ratios, and Wilcoxon p-values. Results show that BFAST generally produced higher mean returns and more favorable risk-adjusted outcomes. For example, Banco Pichincha achieved a mean return of 0.100 under BFAST compared to only 0.001 under CUSUM, while Banco Guayaquil recorded neutral returns with BFAST but losses of –0.170 under CUSUM. BVQ illustrates the risk-adjusted advantage of BFAST, with a Sharpe ratio of –0.292 versus –2.302 for CUSUM, indicating that although both methods generated losses, BFAST mitigated the decline relative to CUSUM. Similarly, firms such as Holcim and Cervecería Nacional showed negative returns under CUSUM that were less severe under BFAST. At the company level, Wilcoxon p-values are generally not significant, reflecting heterogeneity across firms and the limited number of observations, but the consistent advantage of BFAST in mean returns and Sharpe ratios underscores its stronger economic relevance.

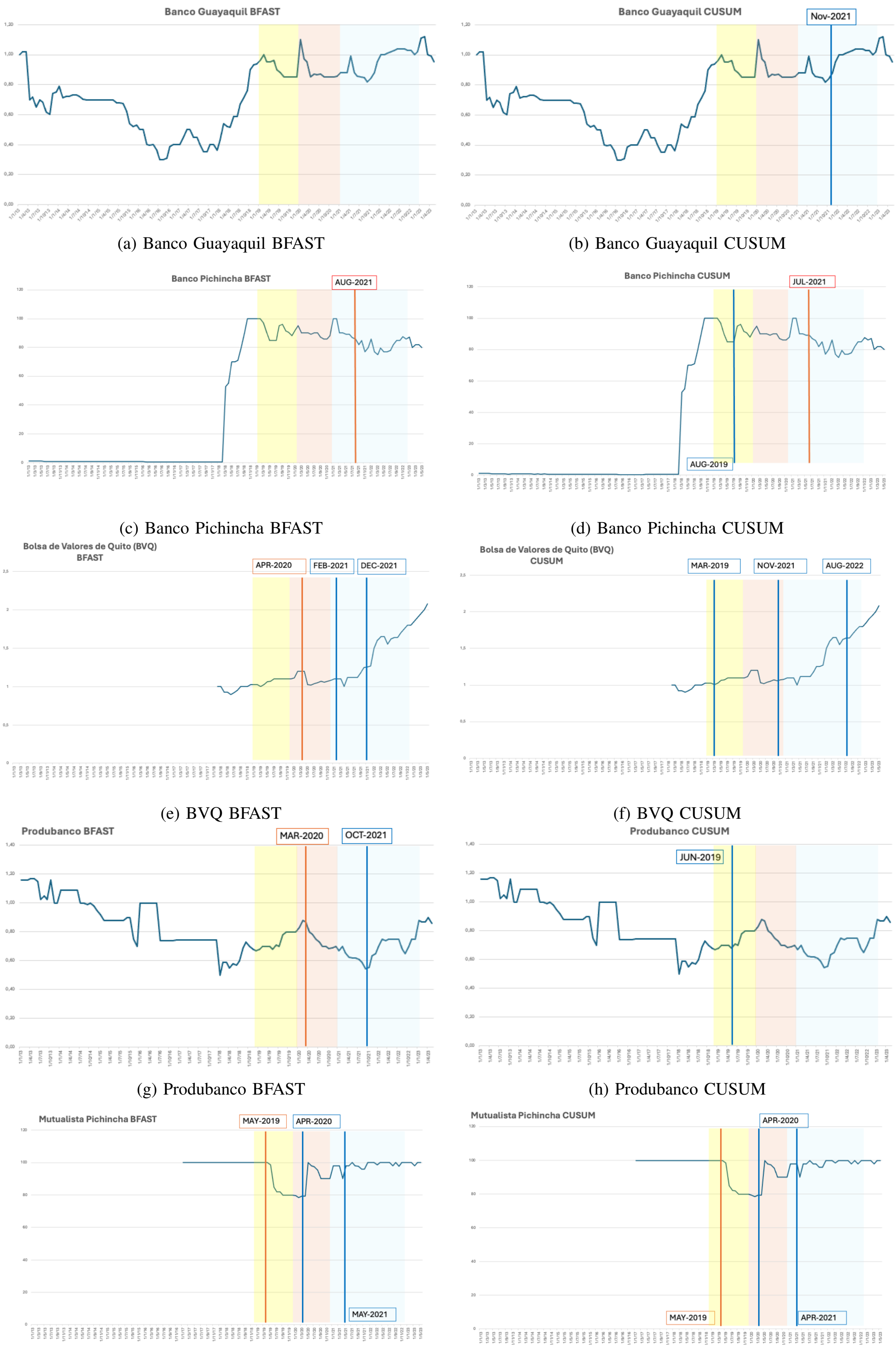
At the aggregate level, Table III confirms the robustness of the advantage of BFAST. Pooled in all firms, BFAST achieved a positive mean return of 0.081 and a Sharpe ratio of 0.560, while CUSUM yielded a negative mean return (–0.016) and a Sharpe ratio of –0.120. Importantly, the Wilcoxon signed-rank test indicates that this difference is statistically significant ($p = 0.005$), providing strong evidence that BFAST signals are economically superior and statistically reliable when evaluated globally.

Taken together, the evidence highlights three key insights: (i) firm-level outcomes vary, with some companies such as Produbanco and Holcim showing strong positive performance while others like BVQ and Cervecería Nacional remain negative; (ii) sectoral heterogeneity influences results, but BFAST consistently mitigates losses and enhances gains relative to CUSUM; and (iii) at the global level, BFAST's superiority is statistically significant and economically relevant. By combining Wilcoxon tests for robustness with Sharpe ratios for risk-adjusted efficiency, the evaluation framework demonstrates that BFAST provides more reliable and effective investment signals than CUSUM in the Ecuadorian market.

D. Breaks Detection Performance

This subsection evaluates the usefulness of structural breaks detected by BFAST and CUSUM as investment signals. Breaks were classified as buy signals when associated with downward trends and as sell signals when linked to upward trends. Each signal was then assessed over a six-month horizon: a buy was considered successful if followed by price increases, and a sell was successful if followed by price declines.

Tables IV–VII present the comparative outcomes. At the sectoral level, both algorithms identified a similar number of breaks, but BFAST consistently achieved a higher proportion of successful signals. In the financial sector (Table



(a) Banco Guayaquil BFAST (b) Banco Guayaquil CUSUM

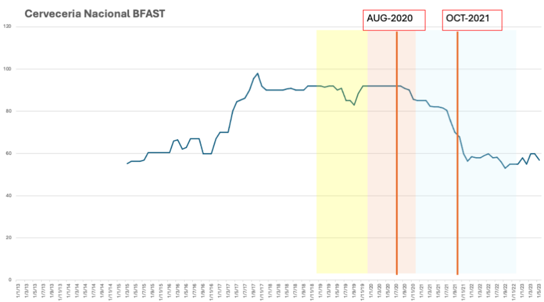
(c) Banco Pichincha BFAST (d) Banco Pichincha CUSUM

(e) BVQ BFAST (f) BVQ CUSUM

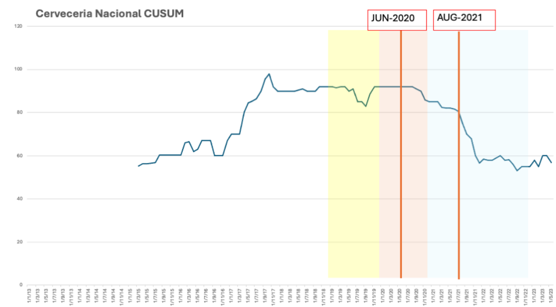
(g) Produbanco BFAST (h) Produbanco CUSUM

(i) Mutualista Pichincha BFAST (j) Mutualista Pichincha CUSUM

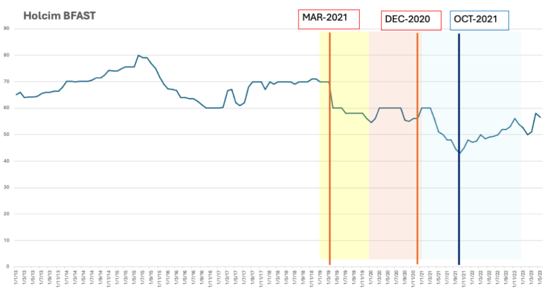
Fig. 2. Displays breakpoint detection for five firms in the financial sector using BFAST (left panels) and CUSUM (right panels). Each vertical line marks the date of a detected structural break. The shaded regions correspond to different phases of the pandemic: yellow indicates the pre-COVID period, red represents the COVID phase, and blue denotes the post-COVID recovery phase. The figure is intended to illustrate the timing and frequency of breakpoints identified by each method; comparative performance is assessed in the accompanying tables rather than inferred directly from these plots.



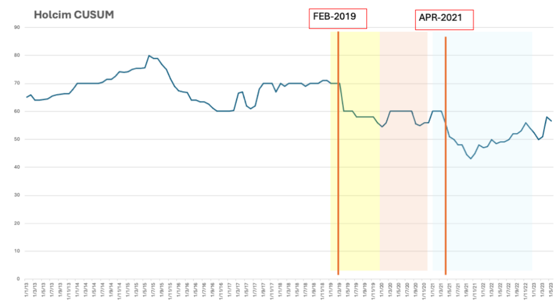
(a) Cervecería Nacional BFAST



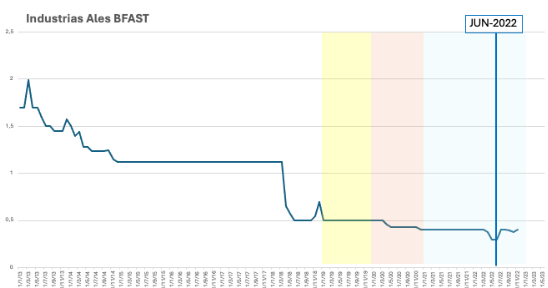
(b) Cervecería Nacional CUSUM



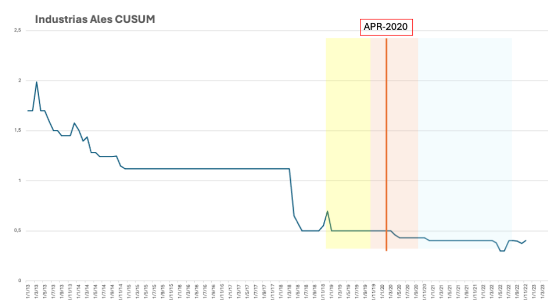
(c) Holcim BFAST



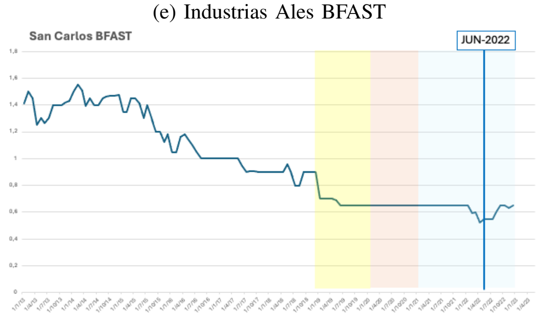
(d) Holcim CUSUM



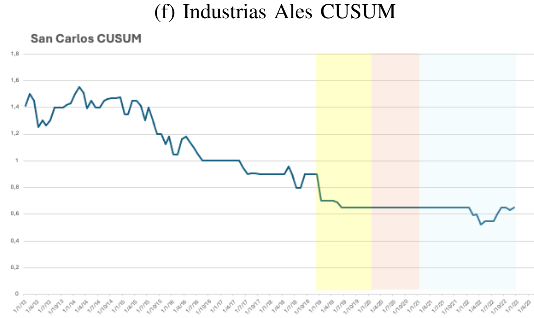
(e) Industrias Ales BFAST



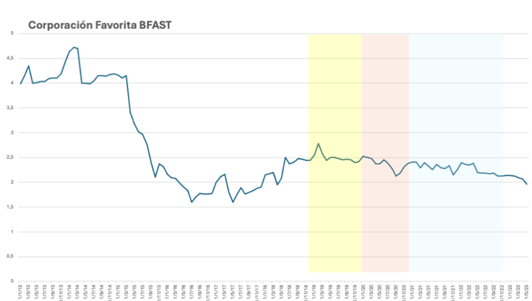
(f) Industrias Ales CUSUM



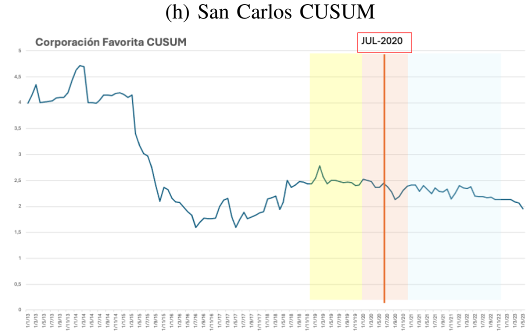
(g) San Carlos BFAST



(h) San Carlos CUSUM



(i) Corporación Favorita BFAST



(j) Corporación Favorita CUSUM

Fig. 3. Displays breakpoint detection for five firms in the productive and commercial sector using BFAST (left panels) and CUSUM (right panels). Each vertical line marks the date of a detected structural break. The shaded regions correspond to different phases of the pandemic: yellow indicates the pre-COVID period, red represents the COVID phase, and blue denotes the post-COVID recovery phase. The figure is intended to illustrate the timing and frequency of breakpoints identified by each method; comparative performance is assessed in the accompanying tables rather than inferred directly from these plots.

TABLE II
COMPANY-LEVEL PERFORMANCE COMPARISON OF BFAST AND CUSUM

Company	Br. BFAST	Mean Return BF	Sharpe BFAST	BR. CUSUM	Mean Return CU	Sharpe CUSUM	Wilcoxon p-value
Banco Guayaquil	0	-	-	1	-0.170	-	0.500
Banco Pichincha	1	0.100	-	2	0.001	-	0.500
BVQ	3	-0.057	-0.292	3	-0.163	-2.302	0.250
Produbanco	2	0.070	-	1	0.120	-	1.000
Mutualista Pichincha	3	0.020	-	3	0.060	-	1.000
Cerveceria Nacional	2	-0.130	-	2	-0.220	-	0.500
Holcim	3	0.100	-	2	-0.230	-	0.500
Industrias Ales	1	0.330	-	1	0.010	-	0.500
San Carlos	1	0.180	-	0	-	-	0.500
Corporacion Favorita	0	-	-	1	-0.010	-	0.500

Br. BF and Br. CU indicate the number of structural breaks detected by each algorithm. Mean Return values are the average of simulated returns from detected breaks. Sharpe Ratios are reported only when at least two observations are available; "—" denotes insufficient data. "—" in the Wilcoxon column indicates the test could not be applied due to limited paired observations. All values are based on Monthly Average Stock Prices (MASP). Sharpe Ratios were computed as $SR = (R_p - R_f/\sigma_p)$ with $R_f = 0$. Negative values indicate that the algorithm produced returns below the risk-free benchmark

TABLE III
PERFORMANCE COMPARISON OF BFAST AND CUSUM AT GLOBAL LEVEL

Method	Mean Return	Sharpe Ratio	Wilcoxon p-value
BFAST	0.081	0.560	0.005
CUSUM	-0.016	-0.120	—

BFAST achieved a positive mean return of 0.081 compared to a negative mean return of -0.016 under CUSUM. The risk-adjusted performance, measured by the Sharpe Ratio, was also substantially higher for BFAST (0.560) than for CUSUM (-0.120), indicating thatBFAST consistently generated excess returns relative to volatility, while CUSUM underperformed even against the risk-free benchmark. The Wilcoxon signed-rank test further validates this difference, with a p-value of 0.005, demonstrating statistical significance at the 1% level. — denotes insufficient paired observations to compute the statistic.

IV), BFAST recorded 7 successful signals out of 9 (78%), compared to CUSUM's 5 out of 10 (50%). In the productive and commercial sector (Table VI), BFAST achieved 6 successes out of 7 (86%), while CUSUM produced only 3 out of 6 (50%). Performance measured over six months reinforces this advantage: BFAST generated average returns of +17% in the financial sector (Table V) and +18.75% in the productive/commercial sector (Table VII), whereas CUSUM produced negative averages in both cases.

TABLE IV
BREAK SUCCESS FOR FINANCIAL SECTOR

Company	BF Br.	CU Br.	BF Suc.	CU Suc.
Banco Guayaquil	0	1	0	0
Banco Pichincha	1	2	1	1
Produbanco	2	1	2	1
BVQ	3	3	1	0
Mutualista Pichincha	3	3	3	3
Total	9	10	7	5

BF Br. and CU Br. indicate the number of structural breaks detected by BFAST and CUSUM, respectively. BF Suc. and CU Suc. represent the number of breaks that were successfully linked to identifiable market events or investment signals. A value of "0" denotes that no successful break was detected for the corresponding company. Totals summarize the aggregate performance across all firms in the financial sector.

Company-level results illustrate this contrast. Produbanco (+42% vs. +13%) and Banco Pichincha (+10% vs. −1%) benefited strongly from BFAST signals, while BVQ remained negative under both methods, though BFAST mitigated losses

TABLE V
PERFORMANCE FOR FINANCIAL SECTOR AT 6 MONTHS WINDOW

Company	BFAST Perf. (%)	CUSUM Perf. (%)
Banco Guayaquil	-	-17
Banco Pichincha	10	-1
Produbanco	42	13
BVQ	-17	-49
Mutualista Pichincha	33	37
Average	17	-3.4

BFAST Perf. and CUSUM Perf. represent the percentage performance of each method over a six-month investment window, calculated from the returns associated with detected structural breaks. Positive values indicate gains, while negative values indicate losses. The symbol "–" denotes that no break was detected or that insufficient data were available to compute performance. The Average row reports the mean performance across all firms in the financial sector. Overall, BFAST achieved a positive average performance of 17%, while CUSUM produced a negative average of –3.4%, underscoring the superior profitability and consistency of BFAST in this sector.

TABLE VI
BREAK SUCCESS FOR PRODUCTIVE AND COMMERCIAL SECTOR

Company	BF Br.	CU Br.	BF Suc.	CU Suc.
Cerveceria Nacional	2	2	1	1
Holcim	3	3	3	2
Industrias Ales	1	0	1	0
San Carlos	1	0	1	0
Corporacion Favorita	0	1	-	0
Total	7	6	6	3

BF Br. and CU Br. indicate the number of structural breaks detected by BFAST and CUSUM, respectively. BF Suc. and CU Suc. represent the number of breaks that were successfully linked to identifiable market events or investment signals. A value of "0" denotes that no successful break was detected for the corresponding company. Totals summarize the aggregate performance across all firms in the financial sector.

(−17% vs. −49%). In the productive/commercial sector, Holcim (+30% vs. −5%) and Industrias Ales (+33%) highlight BFAST's advantage, whereas Cervecería Nacional showed persistent losses under both algorithms. Corporación Favorita further illustrates the limits of break detection, as CUSUM identified a break that did not translate into profitable outcomes.

These patterns underscore the importance of sectoral con-

TABLE VII
PERFORMANCE FOR THE PRODUCTIVE AND COMMERCIAL SECTOR AT 6 MONTHS WINDOW

Company	BFAST Perf. (%)	CUSUM Perf. (%)
Cerveceria Nacional	-6	-15
Holcim	30	-5
Industrias Ales	33	-
San Carlos	18	-
Corporacion Favorita	-	-1
Average	18.75	-7

BFAST Perf. and CUSUM Perf. represent the percentage performance of each method over a six-month investment window, calculated from the returns associated with detected structural breaks. Positive values indicate gains, while negative values indicate losses. The symbol "–" denotes that no break was detected or that insufficient data were available to compute performance. The Average row reports the mean performance across all firms in the financial sector. Overall, BFAST achieved a positive average performance of 18.75%, while CUSUM produced a negative average of –7%, underscoring the superior profitability and consistency of BFAST in this sector.

text. Financial firms exhibited resilience and moderate profitability, reflecting stable cash flows and regulatory oversight, while productive/commercial firms showed greater dispersion, with construction and food processing recovering quickly but beverage production remaining vulnerable to prolonged shocks. Across both sectors, however, BFAST consistently outperformed CUSUM in aligning breakpoints with profitable signals and in generating superior risk-adjusted returns.

These empirical findings are consistent with the theoretical features of BFAST reported by [25]. Its modular decomposition of trend and seasonality enables the algorithm to distinguish persistent structural changes from short-term fluctuations, which explains the superior mean returns and Sharpe Ratios observed in the aggregated results. The iterative break detection mechanism further accounts for the higher number of breaks identified relative to CUSUM, allowing BFAST to capture richer dynamics in illiquid markets. This advantage of BFAST on the quality of structural break detection was previously reported on Earth remote sensing applications [14], [34] and this study has confirmed the same trend on this financial application. Moreover, the statistically significant advantage of BFAST at the global level reflects its robustness in separating genuine structural shifts from noise, a property that is particularly valuable when working with Monthly Average Stock Prices (MASP). Taken together, the results confirm that the theoretical design of BFAST translates directly into empirical superiority, reinforcing its relevance as a methodological contribution for investment strategies in emerging markets.

V. CONCLUSION

This study assessed the potential of structural break detection methods—BFAST and CUSUM—as generators of investment signals in the Ecuadorian stock market during 2019–2022. By combining company- and sector-level analyses with validation through six-month investment windows, Wilcoxon signed-rank tests, and Sharpe ratios, the research provides a comprehensive evaluation of both the statistical robustness and economic relevance of these approaches.

The evidence consistently shows that BFAST outperforms CUSUM. At the firm level, BFAST detected a higher proportion of successful signals and delivered stronger returns, particularly for companies such as Produbanco, Holcim, and Industrias Ales. At the sectoral level, BFAST produced positive average returns in both financial and productive/commercial sectors, while CUSUM signals often led to negative outcomes. When signals were pooled globally, BFAST's advantage was confirmed: the Wilcoxon test indicated statistically significant superiority ($p = 0.005$), and Sharpe ratios highlighted its risk-adjusted efficiency.

Two key contributions emerge from these findings. First, they demonstrate that structural break detection can be transformed into a practical investment tool when signals are validated not only statistically but also economically. Second, they emphasize the role of sectoral heterogeneity: financial firms showed resilience and moderate gains, while productive and commercial firms displayed sharper divergences, with some companies experiencing sustained negative impacts from the COVID-19 pandemic.

In summary, BFAST consistently outperformed CUSUM in detecting structural breaks and generating profitable signals, with positive mean returns and superior risk-adjusted performance. While the reliance on Monthly Average Stock Prices (MASP) was necessary due to the low liquidity of the Ecuadorian market, this limitation smooths short-term volatility and reduces firm-level precision. Even so, the aggregated evidence highlights BFAST's clear advantage and underscores its relevance as a practical tool for investment strategies in emerging markets where sparse trading activity challenges traditional methods. Future research could extend this approach to other contexts by incorporating additional risk metrics, testing alternative break detection algorithms, and exploring its applicability in larger and more liquid markets.

Extending the analysis to daily data would further validate the robustness of BFAST and enhance its applicability in more liquid and dynamic market environments.

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