Statistical characteristics of financial markets in emerging economies

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Abstract: *Financial markets exhibit similar properties called stylized facts. Although the financial markets reflect certain generalized features, they are influenced differently by market changes hence the need for continuous monitoring, reassessment, and analysis. For this reason, we assessed the statistical stylized facts of stocks, and checked how they have gone through regime changes. The study used Markov switching autoregression (MS-AR) model to assess regime changes of 15 stocks sampled from South African, Indian, and Chinese markets. This paper statistically confirmed that stocks in emerging markets follow non gaussian processes, they have fat-tails, are autocorrelated, and experience periodic regime changes triggered by changes in the trading environment.*

Keywords— volatility; non-stationarity; correlation; (G)ARCH model; Markov switching autoregressive (MS-AR) model.

I. INTRODUCTION

Understanding the properties of financial markets is crucial for financial engineers and investors. Empirical studies show that financial returns follow non gaussian distributions which deviates from the normality assumption. Even though the normality assumptions simplify financial modelling processes and led to easier gaussian models, its application may not be realistic in real trading situations. Financial engineers and practitioners have concluded that real financial returns have similar properties called stylized statistical facts. The most common stylized statistical facts of financial markets being volatility clustering, fat-tailed distributions, non-stationarity, serial correlation, and the leverage effect [1][2].

Despite the fact that financial markets reflect certain generalized features, they are influenced differently by market changes hence the need for continuous monitoring, reassessment and analysis.

The project's purpose is thus to investigate and analyze statistical properties of stock markets in emerging nations, with a focus on China, India, and South Africa. The major objective of the study is to use numerous tests of statistical and econometric properties to understand market behavior. The other objective is to analyze stock prices in various time periods to determine the extent to which these markets have undergone regime shifts.

II. THEORETICAL FRAMEWORK

A. Literature review

Financial modelling plays a crucial role in understanding and predicting market behaviour, risk assessment, and investment decision-making. Understanding the characteristics of actual returns on an asset is important for risk management, portfolio improvement, asset value advent and other monetary analysis procedures. Several studies have been done on the characteristics of financial market [2]. These studies show that financial markets exhibit similar properties which are generally called stylized statistical facts. These generalised facts provide a foundation and reference point on which various markets can be analysed.

The most common stylized statistical facts of financial markets are volatility clustering, fat-tailed distributions, non-stationarity, serial correlation and the leverage effect [2].

Volatility Clustering

Volatility clustering is the phenomenon in which intervals of high volatility have a tendency to cluster collectively and intervals of low volatility have a tendency to cluster as well. This stylized fact has been widely studied and documented in financial markets throughout different asset classes and timeframes [2]. The life of volatility clustering demanding situations the regularity assumption in traditional financial models and results in the improvement of models including the autoregressive conditional heteroscedasticity (ARCH) and the generalized autoregressive conditional heteroscedasticity (GARCH) models.

Fat-Tailed Distribution

Previous studies also show that returns on assets usually have fat-tailed distributions; which means that extreme activities arise more often than would be expected in ordinary distributions [1]. This property is called the stylized reality of fat tails or excessive kurtosis. The presence of fat tails has essential implications for risk management because it suggests that extreme activities are more likely than conventional models (along with Gaussian distributions). Numerous techniques including stable distributions and extreme value theory had been used to model and estimate the behaviours of returns on an asset accurately.

Non-Stationarity

Returns on an asset frequently exhibit non-stationary conduct, this means that their facts alternate over time. This stylized fact is typically observed through trends, cycles, and structural breaks in return series. Nonstationary problems are conventional statistical methods that assume that the data is stationary. Researchers have developed a ramification of financial tools, inclusive of root tests, cointegration analysis, and structural break tests, to deal with unstableness and capture modifications in returns on an asset.

Serial Correlation

Serial correlation, or autocorrelation, refers to the dependence of current asset returns on past returns [1]. The presence of serial correlation implies that the current return is related to previous returns, which violates the assumption of independence in traditional models. Autocorrelation is often observed in short-term return data and has implications for market efficiency and trading strategies. Time-series models, such as generalised autoregressive conditional heteroskedasticity (GARCH) models, are commonly used where the variance error is believed to be serially autocorrelated.

Leverage Effect

Leverage effect is a stylized fact that explains the negative relationship among returns on an asset and volatility [2]. Empirical evidence suggests that after volatility increases, returns on an asset have a tendency to decrease and vice versa. The leverage effect is particularly prominent in financial markets, where negative shocks lead to higher volatility and lower asset returns. This stylized fact has implications for pricing models, risk management and portfolio strategies.

In another research we see that traditional financial models usually expect a Gaussian (ordinary) distribution of returns on an asset; however, this distribution can also have tails, skewness, and other irregularities in the financial statements. In his paper titled "Financial Modeling Under Non-Gaussian Distributions," Eric Jondeau explores the importance of incorporating non-Gaussian distributions into financial modeling and proposes numerous techniques and techniques for fixing these problems.

Jondeau's paper offers an in-depth review of the restrictions of the Gaussian models in finance and gives an alternative approach for figuring out non-Gaussian distributions [1]. He added that traditional models based on Gaussian assumptions frequently fail to seize the extreme occasions and heavy-tailed conduct that exists in economic markets. To address those boundaries, Jondeau discusses various methods consisting of the copula models, extreme value theory, and the use of alternative distributional assumptions like stable distributions and generalized hyperbolic distributions. Throughout the paper, Jondeau provides empirical applications to showcase the practical implications of using non-Gaussian distributions in financial modelling. He presents real-world examples and demonstrates how incorporating non-Gaussian assumptions can lead to more accurate risk measures, improved portfolio optimization strategies, and better pricing models for derivative instruments.

The empirical properties of returns on an asset, along with volatility, fat-tailed distributions, non-stationarity, serial coefficients, and leverage results, have been substantially studied. Those stylized facts challenge the assumptions of traditional financial models and feature crucial implications for risk management, portfolio construction, and assets pricing. Researchers have advanced numerous statistical techniques and econometric models to correctly capture these elements. Further studies will provide awareness on enhancing existing models, including new features, and exploring the impact of stylized facts in one-of-a-kind business environments. Understanding these values is important for financial analyst and researchers to make informed economic decisions.

Eric Jondeau's paper, "Financial Modeling Under Non-Gaussian Distributions" is a complete manual guide to understanding the limitations of Gaussian models in finance and the significance of incorporating with non-Gaussian distributions. By exploration volatility models, extreme value theory, and alternative distributional assumptions, Jondeau provides insights via which researchers and practitioners can enhance economic standards. The empirical applications presented in this paper further reinforce the practical relevance of these techniques. Overall, this paper makes an advantageous contribution to financial modeling by means of offering a framework for researchers and practitioners to broaden greater robust models that better capture the complexity of economic transactions.

B. Competitor Analysis

Emerging economies have several strengths which include; rapidly growing financial markets, presenting opportunities for investors and businesses, rapid technological developments and increase in accessibility to global markets and funding. Financial markets in emerging economies attract both domestic and international investors seeking higher returns and diversification. Major weaknesses of emerging economies include economic downturns, inflation, or currency crises which have a negative impact on financial markets and investor sentiment. Financial markets in emerging economies are prone to higher volatility and risks due to factors such as political instability, currency fluctuations, and regulatory uncertainties. The depth and liquidity of financial markets in emerging economies may be relatively lower compared to developed markets, resulting in challenges for large-scale transactions.

The major threats in emerging markets include competition from developed markets, lack of financial data, and inefficiency. Emerging markets also have opportunities in terms of using advanced statistical applications, innovation and data engineering to analyse, manipulate, forecast and generate alphas which increase profitability. Other opportunities include, attractive emerging markets which can attract FDI inflows, supporting market development and infrastructure improvements, and technological innovations which can facilitate financial inclusion, digital payment systems, and online trading platforms, and expanding market access.

In contrast to preceding studies that centred on figuring out the qualitative stylized empirical facts in developed markets, the current study concentrates on quantitatively test those stylized empirical facts against stocks in emerging economies in order to observe notable regime movements or changes in trends over time in these markets.

III. METHODOLOGY

The following methods were followed to achieve the objectives of the study.

A. *Data extraction*

Data for the following companies was extracted;

Table 1 Data Sources

COUNTRY	TICKER	NAME OF INDEX	DATA SOURCE
SOUTH AFRICA	ABGJO	Absa Group Ltd	Yahoo Finance
SOUTH AFRICA	FRSJO	FirstRand Ltd	Yahoo Finance
SOUTH AFRICA	SBKJO	Standard Bank Group Ltd	Yahoo Finance
SOUTH AFRICA	IMPJO	Impala Platinum Ltd	Yahoo Finance
SOUTH AFRICA	LHCJO	Life Healthcare Group Ltd	Yahoo Finance
INDIA	BHARTIARTL	Bharti Airtel Ltd	Yahoo Finance
INDIA	ICICIBANK	ICICI BANK	Yahoo Finance
INDIA	NSEI	NIFTY 50	Yahoo Finance
INDIA	NFTY	First Trust India	Yahoo Finance
INDIA	INFY	Infosys Limited	Yahoo Finance
CHINA	VIPS	Vipshop Holdings Ltd	Yahoo Finance
CHINA	BIDU	Baidu, Inc.	Yahoo Finance
CHINA	NTES	NetEase, Inc	Yahoo Finance
CHINA	TCOM	Trip.com Group Limited	Yahoo Finance
CHINA	TCEHY	Tencent Holdings Limited	Yahoo Finance

We used data for the past ten years (2013 to 2023).

B. Explorative data analysis (EDA)

The principal motive of the EDA is to assist with examining the data before making any assumptions. It enables us to pick out errors, identify patterns in the data, locate relationships among variables. We performed preliminary EDA and normalization and stationary test on our data.

C. *Normality and Non-Normality assessments*

The Shapiro-Wilk test was used to assess whether a data set fits a normal distribution. The normal distribution, is a symmetric probability distribution that is characterized by its mean and standard deviation. Analysis of normality is important in many statistical analyses because many statistical methods assume that data come from a normal distribution.

Here's how the Shapiro-Wilk test works:

Null Hypothesis (H0): Data is normally distributed.

Alternative Hypothesis (H1): Data is not normally distributed.

Test Statistic**:** The Shapiro-Wilk test statistic (W), calculates the discrepancy among the observed and the expected values. The formula for test statistic is given as follows

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_i\right)^2}{\left(\sum_{i=1}^{n} (x_i - \bar{x})^2\right)}$$

Where:

- n: sample size.
- $x_{(i)}$: ith order statistic (the ith smallest value) of the sample.
- x_i: ith data point.
- $\bar{x}$: sample mean.
- a_i: constants that depend on the sample size and are used to give more weight to values in the middle of the distribution.

P-value: The test statistic is compared to critical values to obtain a p-value. The p-value represents the probability of observing the test statistic or something more extreme under the assumption that the data comes from a normal distribution. A small p-value suggests that the data significantly deviates from a normal distribution, leading to the rejection of the null hypothesis.

Interpretation: When the p-value is less that the level of significance (LOS), then we reject the null hypothesis and accept the alternative hypothesis.

D. *Stationarity and non-stationarity examination*

Stationarity is a crucial concept in time series analysis, especially when dealing with financial data like stock prices. Stationarity means that the statistical properties of data such as mean, variance, and autocorrelation, remain constant over time. Non-stationary data exhibit trends, seasonality, and varying statistical properties.

We used the Augmented Dickey-Fuller (ADF) test to determine the stationarity of our data. The Dickey-Fuller test is used to see if there is unit root in our data. The ADF is an extension of the standard Dickey-Fuller test, where as we can apply ADF on a large sized set of time series models.

Working of Augmented Dickey-Fuller test:

Null Hypothesis (H0): Data has unit root and is non-stationary.

Alternative Hypothesis (H1): Data doesn't have uit root and is stationary.

Test Equation**:** The ADF test is conducted using a regression equation of the form [9]:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t$$

Where:

- Δyt is the first difference of the time series at time t.

- α is a constant term.
- βt captures the deterministic time trend.
- γ is the coefficient of the lagged level of the time series.
- δ1, δ2, ..., δp−1 are the coefficients of the lagged first differences up to lag p−1.
- εt is the residual (error term) at time t.

Test Statistic: The ADF test computes a test statistic which is compared to critical values to determine the stationarity of the data. If it's less negative or positive, you fail to reject the null hypothesis, indicating non-stationarity.

Critical Values: The critical values depend on the significance level you choose (common choices are 1%, 5%, and 10%) and the sample size of your data. These values are pre-determined based on mathematical calculations and tables.

Interpretation: If the calculated test statistic is more negative than the critical values, you can conclude that the data is stationary and does not have a unit root, indicating that it's suitable for time series analysis. If the test statistic is less negative or positive, it suggests that the data is non-stationary and may require differencing or other transformations to make it suitable for analysis.

E. (G)ARCH model

One key property of financial market is volatility. ARCH and GARCH models are used to model stock volatility. The term ARCH refers to autoregressive conditional heteroscedasticity. Given that $\in_t$ is a Gaussian white noise, with a variance of one, and mean of zero, then a_t is an ARCH(q) process if;

$$\alpha_t = \delta_t \epsilon_t \qquad [1]$$

Given that;

$$\delta_t = \sqrt{\alpha_0 + \sum_{i=1}^{q}(\alpha_i\, \alpha_{t-i}^2)} \qquad [2]$$

Equation 2 is a conditional standard deviation of at a time t, given past returns.

An ARCH model can be extended into Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. GARCH model generalizes the ARCH model. A process follows a GARCH (p, q) model if;

$$\alpha_t = \delta_t \epsilon_t \quad [3]$$

Where;

$$\delta_t = \sqrt{\alpha_0 + \sum_{i=1}^{q}(\alpha_i\, \alpha_{t-i}^2) + \sum_{i=1}^{p}(\beta_i\, \delta_{t-i}^2)} \qquad [4]$$

Where:

- δ_t: conditional standard deviation at time t.
- q: error terms.
- p: variance order.
- α_0: constant.
- α_i: coefficient for the error term at t-i.
- β_i: co-efficient for the variance at time t-i.

In this study, a GARCH (1, 1) was adopted and it can be generalized as;

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{q}(\alpha_i\, \alpha_{t-i}^2) + \sum_{i=1}^{p}(\beta_i\, \delta_{t-i}^2) \qquad [5]$$

F. Markov switching autoregressive (MS-AR) model

One of the objectives of the study was to identify regime shifts in our stocks. An MS-AR model is given as;

$$y_t = \mu_{st} + x_t\alpha + z_t\beta_{st} + \sum_{i=1}^{p}\emptyset_{i,st}(y_{t-i} - \mu_{st-i} - x_{t-i}\alpha - z_{t-i}\,\beta_{st-1}) + \varepsilon_{st} \qquad [6]$$

Where:

- y_t: dependent parameter at time t.
- μ_{st}: state-dependent vector.
- x_t: covariates whose coefficient is α.
- α: are state-invariant.
- z_t: covariates whose coefficients is β_{st}.
- β_{st}: state-dependent.
- $\emptyset_{i,st}$: ith autoregressive term.
- μ_{st-i}: intercept corresponding to the state that the process was in at period t − i.
- β_{st-1}: coefficient vector on z_{t-i}.
- z_{t-i} corresponding to the state that the process was in at period t – i.
- ε_{st}: normal error with mean 0 and state-dependent variance [6].

IV. RESULTS

We present the key statistical characteristics of financial markets in emerging economies based on our analysis. We extracted the data from yahoo finance for five stocks of three countries each for a decade. Then we checked for null values and we replaced missing values by using the values before them. Then we calculated the returns and log returns for the data and we started the analysis.

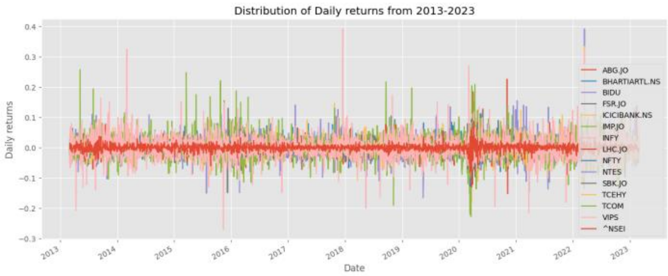

Fig 1 Distribution of Daily returns from 2013-2023

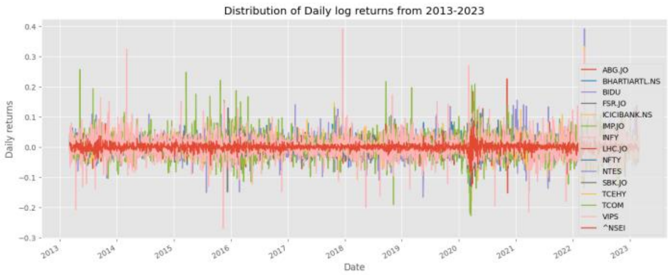

Fig 2 Distribution of Daily log returns from 2013-2023

Our results show that our data sets come from non-gaussian distributions. The returns are not normally distributed. This proves one of the stylized facts on returns which states that stock returns are not normally distributed. P value is less than the threshold, alpha of 0.05 then there is enough evidence that the data set is not coming from a normal distribution. We also carried out kurtosis test on the data and the results came positive and above zero. This shows that all the tested stocks in emerging markets have fat-tails.

Correlation matrix results shows that generally stocks in emerging markets, South Africa, India and China move in the same direction, with those in the same country more correlated to each other. The results are shown below.

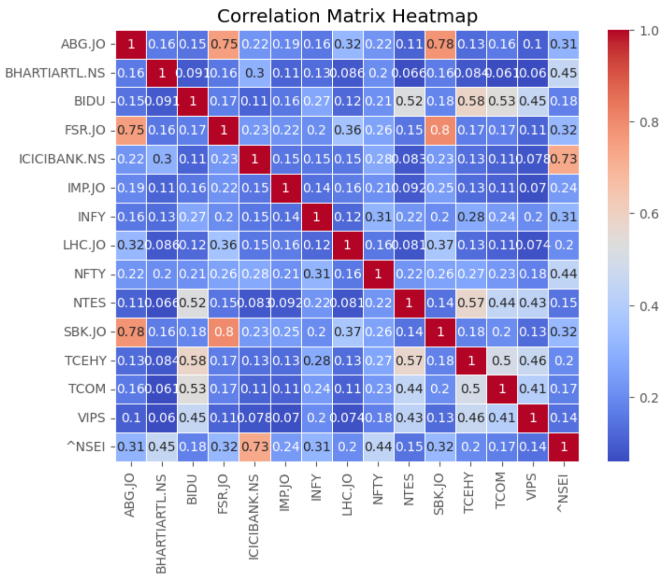

Fig 3 Correlation Matrix

We also tested the stationarity of our data using ADF tests. Results show that all log-returns of stocks are stationary. Stationary time series allow for more reliable statistical inference, including hypothesis testing, confidence intervals, and parameter estimation. Our data as shown on figure 1 and figure 2 exhibits volatility clustering. We also plotted ACF and PACF of returns as shown by the figure below.

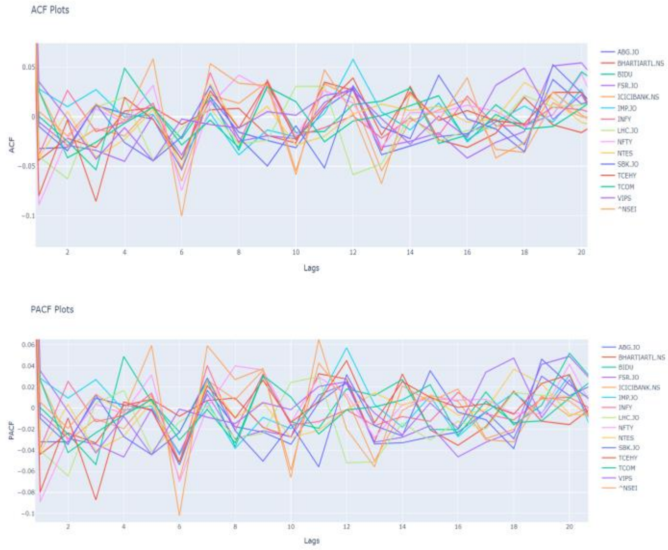

Fig 4 ACF & PACF

ACF and PACF plots show that our data is autocorrelated and follow an autoregressive moving average process. This makes GARCH model an appropriate model to analyse the time series data.

Now moving forward, we divided our data country wise and applied GARCH and Markov switching autoregression (MS-AR) models and analyse the results. By splitting the data, we got to identify the regime changes in each country and tried to understand a logical reasoning for the changes.

We built a GARCH (1,1) model and the table shows the summary of the results.

Table 2 GARCH (1,1) results (summary)

STOCK	OMEGA	ALPHA	BETA	PVALUE[P>|T|]
ABGJO	9.2472e-06	0.1000	0.8800	0.256
FRSJO	8.4923e-06	0.0500	0.9300	5.393e-20
SBKJO	8.0118e-06	0.0500	0.9300	0.000
IMPJO	2.3720e-05	0.0500	0.9300	4.820e-32
LHCJO	7.1420e-06	0.0500	0.9300	0.000
BHARTIARTL	4.1323e-05	0.0500	0.8500	2.501e-119
ICICIBANK	9.4068e-06	0.0500	0.9300	0.000
NSEI	2.3525e-06	0.1000	0.8800	0.000
NFTY	4.0314e-06	0.0500	0.9300	0.000
INFY	9.8258e-05	0.2138	0.4914	2.388e-03
VIPS	3.3586e-04	0.0878	0.6681	0.132
BIDU	5.5455e-05	0.0500	0.8500	8.923e-27
NTES	5.6220e-05	0.0500	0.8500	7.387e-39
TCOM	1.4462e-05	0.0100	0.9700	0.000
TCEHY	4.2282e-05	0.1000	0.8000	9.452e-46

P-values show the validity of the GARCH model used. All our p-values are zero or near zero which show that all of our parameters, Omega, Alpha and Beta for all stocks are statistically significant. Generally, stocks with a higher Alpha plus Beta tends to be spikier. From our GARCH (1,1), we also discovered that all our stocks are mean reverting, that means Alpha plus Beta of all stocks was found to be less than 1. ALjung-Box test was done to assess the overall randomness or autocorrelation of standardized residuals. The model was able to remove autocorrelation from five (5) stocks IMP.JO, LHC.JO, VIPS, NTES, and TCOM. P values of these stocks were found to be less than 5% which means the residuals were just white noise and the model fitted well. We also discovered the leveraged effect in our results after checking the 50-day rolling volatilities of our stocks.

We then checked regime changes of stocks from 2013 to 2023. We implemented a Markov switching autoregressive (MS-AR) model. We then plotted the graphs to show the probabilities of high variance and probabilities of low variance. We observed that stocks in SA, India and China have gone through several regime changes from 2013 up to 2023. The following graphs shows the regime changes that stocks in these economies have gone through. One notable regime change that occurred in all economies happened between 2020 and 2021. All stocks responded the same as depicted on Figure 6, 7 and 8. Stocks in all the economies also went through two regime changes at same times in 2013. Even though there are instances where stocks in these economies behave the same, it can also be seen that stocks in the same economy have more similar behavior and have undergone more similar regimes from 2013 to 2023.

Fig 5 Stocks regime changes in South African economy

Fig 6 Stocks regime changes in Indian economy

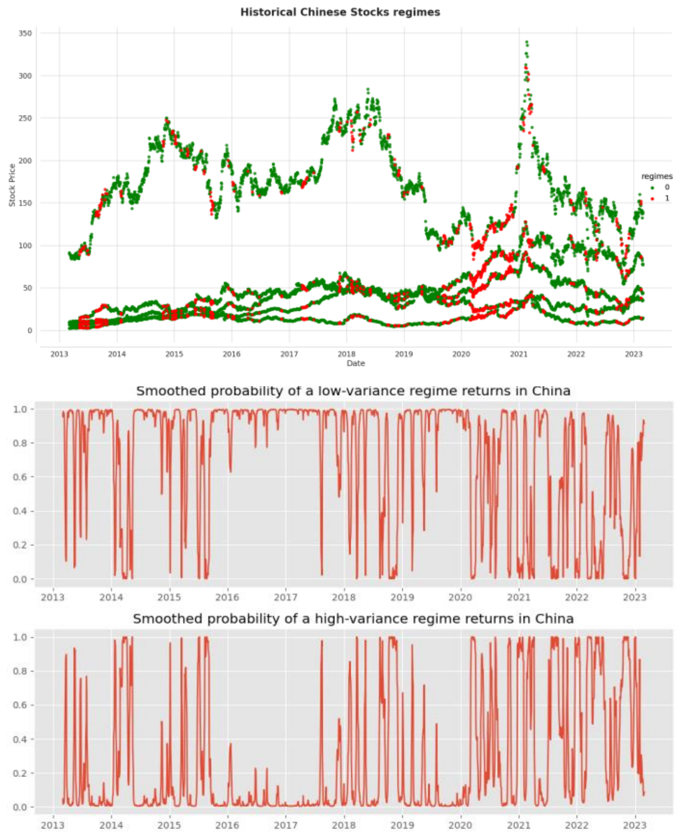

Fig 7 Stocks regime changes in Chinese economy

V. DISCUSSION

This paper analyzed statistical characteristics of financial markets in emerging economies with a particular reference to the Chinese, Indian and South African markets. Firstly, we discovered that financial returns in emerging markets are not normal but have fat-tails. This corroborated with previous empirical studies [1]. The main implication of this result is the application of fat-tails in financial modeling which is divorced from the notion of gaussian distributions. Fat-tails show that there is the probability of extreme outcomes being above normal. This means that extreme outcomes have greater impact on expected risk of standard deviation of returns. Financial engineers can then use this idea to calculate metrics like Value at Risk (VaR) and Expected Shortfall (ES) [2].

We also analyzed correlations between stocks and realized that most stocks within the three economies, India, South Africa, and China move in the same direction, they are positively correlated. This could be attributed by the fact that India, China, and South Africa are members of the BRICS bloc. This corroborated with previous findings which shows that stocks in BRICS countries behave in similar ways [7]. The implication of this statistical property is on creation of portfolios as investors will need to consider the issue of risk minimization and invest in markets which behave in different ways. Investors will therefore need to invest in different markets rather than placing all their funds within South Africa, China and India.

This paper also confirms that log-returns of sampled stocks in emerging markets are stationary. Stationarity is a key statistical property in finance as it enables construction of stable models. GARCH (1,1) was able to model our data and results show its validity in analyzing financial data. GARCH (1,1) model is a simple and less expensive model that can be used to analyze volatility of stocks. From our GARCH (1,1) model we discovered that stocks in emerging markets (India, SA and China) are mean reverting. Mean reversion means that stock prices return to the mean after deviating for a certain period of time due to any significant changes on the market. The model was able to capture both the arch effect and conditional heteroskedasticity of our data. We also observed the leveraged effect in our results. We observed that after volatility increases, returns on an asset decrease and after volatility decreases, returns increase. This corroborated with previous empirical studies and this property is regarded as one of the stylized properties of stock returns [2]. The leverage effect is particularly prominent in financial markets, where negative shocks lead to higher volatility and lower asset returns.

This paper also analyzed how stocks in emerging markets have undergone regime changes. Stocks in India, China and South Africa all faced two extreme regime changes in 2013. This could be attributed to the wider global recession period which happened in 2013 [8]. This was caused by initial subprime mortgage crisis and the following recession and policy changes in the United States of America. The Chinese markets have also undergone regime changes in 2015 and 2016. This regime change coincided with the announcement of drafted laws by Chinese government to control shadow-financed margin accounts in 2015, which triggered the 2015 to 2016 Chinese stock market meltdown [8]. Chinese markets also show changes in market regimes in 2018. This period coincided with the US-China trade wars which led to the crush of Chinese markets in 2018 [7]. It can therefore be explained that statistical properties of markets can be used to analyze markets and make objective decisions.

VI. CONCLUSION

The aim of this paper was to statistically assess the stylized facts of stocks, and check how they have gone through regime changes. The paper made the following conclusions.

Using the Augmented Dickey-Fuller test, we discovered that stock prices do not follow gaussian processes. Through statistical normality tests, we discovered that our data sets were not normal. This corroborated with previous empirical studies which also shows that stock prices follow non-gaussian processes.

We discovered that our data sets have fat-tails. Through statistical kurtosis tests, all our data sets had positive high kurtosis which shows that an investment in South African, Indian, and Chinese stocks will yield occasional extreme returns, which can be negative or positive.

We tested how stocks in emerging markets are correlated. Through correlation tests, we discovered that stocks in emerging markets, South Africa, India, and China move in the same direction, with those in the same country more correlated to each other.

We tested the stationarity of our data using ADF tests. We discovered that all log-returns of tested stocks were stationary. Stationary time series allow for more reliable statistical inference, including hypothesis testing, confidence intervals, and parameter estimation.

We tested for autocorrelation of our stocks. We discovered that returns in all the tested stocks were autocorrelated and followed autoregressive moving average processes.

We also discovered that all returns in India, China, and South Africa have signs of volatility clustering. We discovered that volatility of stocks has persistence, having periods of high volatility and periods of low volatility.

We found white noise in some of our data residuals which shows the ability of GARCH (1,1) model in analyzing and modeling autocorrelated data. Though GARCH (1,1) was able to model our data, we recommend higher and more advanced GARCH models to account for ARCH effects in all stocks as we also discovered presence ARCH effects in some of our residuals, which is a sign that more robust and varied model could have performed better.

We confirmed the leverage effect in financial markets, where a decrease in volatility leads to increase in stock returns and an increase in volatility results in decrease of stock returns.

Finally, the paper discovered that stocks in emerging markets, India, South Africa, and China have undergone different regime changes due to several reasons like outbreak of COVID-19, and change in policies within different economies which triggered financial shocks.

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Source Code: https://github.com/Vivek221B/Statistical-characteristics-of-financial-markets-in-emerging-economies-.git