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A Study On Volatility and Tail Risk of Small-Cap Companies in Comparison to Big-Cap Companies

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Abstract: The generalized autoregressive conditional heteroskedasticity (GARCH) framework analysis was used to examine the volatility and tail risk of small-cap companies in comparison to large-cap companies. This study examines three large-cap stocks and three small-cap stocks. Daily closing data, alternatively referred to as return, will be analysed in this study. Correspondingly, the performance of small- and large-cap companies is susceptible to volatility and tail risk. As a result, we compared the volatility factor of small- and large-cap companies. This approach was chosen based on the GARCH (1,1) model's simplicity. All calculations were performed using the statistical tool RStudio.

Keywords: Small-Cap Companies, Big-cap Companies, Volatility and Tail Risk

1. Introduction

Large-cap firms, sometimes known as large-cap stocks, are corporations with a more significant market capitalization. In this context, the market refers to the company's total market price, which can be calculated by multiplying the stock price by the total number of shares issued. On the other hand, small-cap firms, sometimes known as small-cap stocks, engage in burgeoning sectors. Small-cap firms may achieve faster sales growth than large-cap firms because they need a smaller earnings foundation, which is often more volatile and susceptible to economic fluctuations. Due to their size, they have a higher chance of surviving the challenging economic environment than equities with lower market capitalizations. As a result, they are considered riskier investments than huge stocks. Volatility in the local stock market undoubtedly has ramifications for financial and economic activity.

Abor [1] stated that the relationship between company capitalisation and financial performance and the stock return has revealed that both large and small enterprises have their own set of benefits and disadvantages. Larger organisations have a considerable competitive advantage over smaller firms in terms of market share, the capacity to take advantage of bulk buy offers or projects needing higher capital rates, and the potential to earn a higher profit margin.

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Volatility is a statistical measure of the dispersion of returns for a given security where the higher the volatility, the riskier the security [2]. Volatility is often measured as either the standard deviation or variance between returns from that same security or market index [3]. Tail risk is a form of portfolio risk that arises when the possibility that an investment will move more than three standard deviations from the mean is greater than what is shown by a normal distribution.

According to Brahma [4], the influence of company size on financial performance and the stock return has long been a source of contention among academics and investment practitioners. Companies are classified according to their market capitalisation. Large stocks are often market leaders in their industries or sectors and represent well-known mature corporations.

Engle [5] utilised daily closing price data from the Dow Jones Industrial Index (DJIA) to find a decent volatility model that can foresee and encapsulate frequently accepted stylised truths about conditional volatility. The stylised facts include volatility persistence, mean-reverting behaviour, the asymmetric effect of harmful vs positive return innovations, and the likelihood of exogenous or pre-determined variable points having a significant impact on volatility.

To address the objectives of this study focuses on the behavior of small-cap and big-cap companies during a specified period (2019-2021). In addition, this study focuses on the volatility factor and tail risk will help to increase the knowledge on the levels of volatility and tail risk on small-cap in comparison to big-cap companies. An understanding of levels of volatilities and tail risk on small-cap companies in comparison to big-cap companies will help investors and fund managers to identify opportunities for portfolio diversification.

2. Materials and Methods

2.1 Data Description

The dataset was obtained from Yahoo Finance by using RStudio. The volatility of small-cap and big companies was simulated using a GARCH approach. The approach was selected using the relatively modest GARCH (1,1) model. All computations were carried out using the RStudio statistical tool.

Large-cap companies

1. APPLE INC. - (TICKER: AAPL)

Market Capitalization: $2.941 Trillion

Apple Inc. is a technology company based in California that develops and sells personal computers, smartphones, and consumer electronics, as well as operating systems and application software. Apple also operates online music, film, and software sales portals. Apple's market capitalization is $2.941 trillion as of December 2021.

2. ALPHABET INC. - (TICKER: GOOG)

Market Capitalization: $1.943 Trillion

A In 2015, Google established a corporate structure under the new holding company and moniker Alphabet. Alphabet Inc. is the publicly traded holding company in the United States of America for the former Google LLC, which continues to exist as a subsidiary. Mountain View, California is home to the company's headquarters. Sundar Pichai serves as CEO of the company. Alphabet (Google) had a market capitalization of $1.943 trillion as of December 2021.

3. TAIWAN SEMICONDUCTOR MANUFACTURING COMPANY, LIMITED - (TICKER: TSM)

Market Capitalization: $633.01 Billion

Taiwan Semiconductor Manufacturing Company, Limited is the third largest semiconductor manufacturer in the world, and the largest contract manufacturer of semiconductor products in the world. In 1987, the company was founded. The company's headquarters and primary operations are based in Hsinchu, Taiwan. TSMC has a market capitalization of $633.01 billion as of December 2021.

Small-cap companies

1. RIOT BLOCKCHAIN INC. - (TICKER: RIOT)

Market Capitalization: $2.77 Billion

Riot Blockchain, Inc. is a Bitcoin mining company that is rapidly expanding its large-scale mining operations in the United States. Riot Blockchain had a market capitalization of $2.74 billion as of December 2021.

2. INDIAN ENERGY EXCHANGE LTD. – (TICKER: IEX)

Market Capitalization: $3.03 Billion

IEX is India's first and largest power exchange. It commands a market share of more than 98 percent of electricity traded volume and a diverse participant base of more than 6300. By providing an automated trading platform for the physical delivery of electricity, Renewable Energy Certificates (RECs) and ESCerts (Energy Saving Certificates). Indian Energy Exchange had a market capitalization of $3.03 billion as of December 2021.

3. KULICKE AND SOFFA INDUSTRIES INC. – (TICKER: KLIC)

Market Capitalization: $3.64 Billion

Kulicke and Soffa Industries, Inc. designs, manufactures, and sells semiconductor assembly capital equipment and tools. Capital Equipment and Aftermarket Products and Services are the company's two segments (APS). The company manufactures and sells advanced displays; advanced packaging products such as die-transfer, flip-chip, and TCB; ball bonder, die-attach, electronics assembly, lithography, wafer-level bonder, and wedge bonder; consumables such as capillaries, dicing blades, and wedge bonds; and auto offline programming. Kulicke and Soffa Industries had a market capitalization of $3.65 billion as of December 2021.

2.2 Volatility factor and Tail Risk

Financial time series data demonstrates particular traits and trends, according to studies. These traits and patterns have been critical in identifying, specifying, estimating, and forecasting particular trends in the data under study, as well as in subsequent studies and research. Volatility models must be capable of capturing and expressing these stylized facts. The following are some common stylized facts seen in markets, financial instruments, and bonds:

1. Volatility clustering: Salamat, *et al.* [5] has stated that volatility clustering, one of the most important stylized facts in financial markets, refers to the observation that large price changes are typically followed by subsequent large price changes, while slight price changes are typically followed by subsequent small price changes.

2. Mean Reverting: (Fouque, [6] state that mean reversion is a financial term that refers to the assumption that the price of an asset will tend to converge to its mean over time. A measure of persistence in a volatility model is determined by observing the half-life of the volatility. Half-life volatility a measurement that calculates the duration of volatility’s return to its average after a shock.

3. Fat Tail Distribution: Tail risk, sometimes called "fat tail risk," is the financial risk of an asset or portfolio of assets moving more than three standard deviations from its current price, above the risk of a normal distribution. Tail risk as excess kurtosis, this property of the unconditional distribution in return data was observed when the return deviation deviated consistently from normality.

4. Apart from the above listed stylized facts, there are others such as co-movements of volatilities across markets and assets as well as long memory properties.

2.3 Method of Analysis

The generalized autoregressive conditional heteroskedasticity (GARCH) is a statistical model that can be used to analyze a number of different types of financial data. Financial institutions typically use this model to estimate the volatility of returns for stocks. The Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. With standard time series regression models, which assume a constant variance, the GARCH model allowed the error factor's variance to vary with time.

The GARCH model successfully models the time-series behaviour of stock returns because it allows for the conditional variance to be a function of both the preceding period has squared errors and its past conditional variances [7]. Volatility was an essential component of financial modelling, and GARCH modelling was unquestionably the best platform for estimating since it allowed for the inclusion of several data attributes.

The equity return is calculated

$$R_t = \ln(P_t) - \ln(P_{t-1}) \qquad Eq.1$$

where,

- R_t is equity return
- P_t is daily closing price of company during period t
- P_{t-1} is daily closing price of company during period $t-1$

As previously stated, the volatility of small-cap and big companies was simulated using a GARCH approach. The approach was selected using the relatively modest GARCH(1,1) model. All computations were carried out using the RStudio statistical tool.

Step 1: The large cap and small cap companies will estimate with an ARCH and a GARCH term. The conditional mean states as follows:

$$Y_t = x_t^2\theta + \varepsilon_t \qquad Eq.2$$

where,

- Y_t is conditional mean
- x_t is vector of exogeneous variable.

The conditional variance equation GARCH (1,1) model states as follow:

The conditional variance is

$$\sigma^2 = \omega + \alpha\varepsilon_t^2 + \beta\sigma_t^2 \qquad Eq.3$$

where,

- ω is a constant term
- $\alpha\varepsilon_t^2$ is ARCH term

- $\beta\sigma_t^2$ is GARCH term

Step 2: By carrying the GARCH model analysis, Specification of GARCH is given by the following equation,

$$\log\sigma_t^2 = \omega + \beta\, log\sigma_t^2 + \alpha\left|\frac{\varepsilon_t}{\sigma_t}\right| + \gamma\frac{\varepsilon_t}{\sigma_t} \qquad Eq.4$$

Step 3: The volatility model is then apply to optional tests in RStudio.
Step 4: Daily closing price data from the previous two years was used to convert to daily return. By utilising RStudio to obtain empirical data and create a discussion and conclusion. The study analysed the distribution of market returns over a two-year period.

3. Results and Discussion

3.1 Descriptive Analysis

In this chapter the results and computer analysis output will be discussed in detail. Detailed descriptive analysis and specifics analysis will be provided if necessary. In this study the small-cap and big-cap companies were analysed, a total 6 sets of data were used. The samples for daily closing return retrieved from the Yahoo Finance were AAPL (Apple Inc,), GOOG (Alphabet Inc.), TSM (Taiwan Semiconductor Manufacturing Company, Limited), RIOT (Riot Blockchain Inc.), IEX (Indian Energy Exchange Ltd.) and KLIC (Kulicke and Soffa Industries Inc.). The generalized autoregressive conditional heteroskedasticity, GARCH(1,1) model is applied for the small-cap and big-cap companies.

3.2 Emprirical Result and Analysis on Volatility and Tail Risk

3.2.1 Apple Inc. - A

Table 3.1: AAPL returns descriptive statistics from 2018-01-01 to 2021-01-01

DATA	505
MEAN	0.002692597
SKEWNESS	-0.1971591
KURTOSIS	5.791033
JARQUE-BERA	707.52 with P-value= 0.000000

Source: RStudio Analysis Output

Table 3.2 Result from the GARCH (1,1) for AAPL

COEFFICIENT	COEFFICIENT FACTOR	STANDARD ERROR	P-VALUE
ω	0.000021	0.000008	0.005279
α	0.179643	0.041025	0.000012
β	0.785333	0.038418	0.000000
$\alpha+\beta$	0.964976	-	-
μ	0.003787	0.000730	0.000000

Source: RStudio Analysis Output

A total of 505 daily returns were studied for two years period between January 2019 and January 2021. The Jarque-Bera test value of 707.52 indicated significant departures from normality for the stock. The return statistics and the GARCH (1.1) outputs are summarized in Tables 3.1 and 3.2. The statistics showed that the company had a positive return of about 0.002692597 (0.269%) per day. According to John, [7], the $\alpha + \beta$ is 0.964976 implied that the volatility half-life is 21 days. It could be concluded that the volatility has a long memory which is persistent and mean-reverting [8]. The skewness for AAPL is -0.1971591 which is negatively skewed. The negative skewness of the distribution indicates that an investor may expect frequent small gains and a few large losses [9].

3.2.2 Alphabet Inc.- GOOG

Table 3.3: GOOG returns descriptive statistics from 2019-01-01 to 2021-01-01

DATA	505
MEAN	0.001227546
SKEWNESS	-0.06638783
KURTOSIS	6.096737
JARQUE-BERA	780.94 with P-value= 0.000000

Source: RStudio Analysis Output

Table 3.4 Result from the GARCH (1,1) for GOOG

COEFFICIENT	COEFFICIENT FACTOR	STANDARD ERROR	P-VALUE
ω	0.000053	0.000019	0.005712
α	0.162515	0.065600	0.013236
β	0.695024	0.099913	0.000000
$\alpha + \beta$	0.857539	-	-
μ	0.001874	0.000722	0.009440

Source: RStudio Analysis Output

A total of 505 daily returns were studied for two years period between January 2019 and January 2021. The Jarque-Bera test value of 780.94 indicated significant departures from normality for the stock. The statistics showed that the company had a positive return of about 0.001227546 (0.122%) per day. According to John, [8] the $\alpha + \beta$ is 0.9676 implied that the volatility half-life is 6 days. It could be concluded that the volatility has a long memory. The skewness for GOOG is -0.06638783 which is negatively skewed with expect frequent small gains and a few large losses.

3.2.3 Taiwan Semiconductor Manufacturing Company Limited - TSM

Table 3.5: TSM returns descriptive statistics from 2019-01-01 to 2021-01-01

DATA	505
MEAN	0.002439482
SKEWNESS	0.01395352
KURTOSIS	5.623184
JARQUE-BERA	664.04 with P-value= 0.000000

Source: RStudio Analysis Output

Table 3.6 Result from the GARCH (1,1) for TSM

COEFFICIENT	COEFFICIENT FACTOR	STANDARD ERROR	P-VALUE
ω	0.000087	0.000024	0.000343
α	0.310261	0.078252	0.000073
β	0.516999	0.092268	0.000000
$\alpha + \beta$	0.827260	-	-
μ	0.002651	0.000765	0.000532

Source: RStudio Analysis Output

A total of 505 daily returns were studied for two years period between January 2019 and January 2021. The Jarque-Bera test value of 664.04 indicated significant departures from normality for the stock. The statistics showed that the company had a positive return of about 0.002439482 (0.243%) per day. According to John, [8], the $\alpha + \beta$ is 0.827260 implied that the volatility half-life is 11 days. It could be concluded that the volatility, which is persistent and mean-reverting. The skewness for TSM is 0.01395352 which is positively skewed with expect frequent large gains and a few small losses.

3.2.4 Riot Blockchain Inc. - RIOT

Table 3.7: RIOT returns descriptive statistics from 2019-01-01 to 2021-01-01

DATA	505
MEAN	0.007441185
SKEWNESS	1.181442
KURTOSIS	5.383604
JARQUE-BERA	725.89 with P-value= 0.000000

Source: RStudio Analysis Output

Table 3.8 Result from the GARCH (1,1) for RIOT

COEFFICIENT	COEFFICIENT FACTOR	STANDARD ERROR	P-VALUE
ω	0.000038	0.000031	0.215388
α	0.045629	0.012697	0.000326
β	0.953371	0.012423	0.000000
$\alpha + \beta$	0.999000	-	-
μ	0.001451	0.003043	0.633529

Source: RStudio Analysis Output

A total of 505 daily returns were studied for two years period between Jan. 2019 to 2021. The Jarque-Bera test value of 725.89 indicated significant departures from normality for the stock. The statistics showed that the company had a positive return of about 0.007441185 (0.744%) per day. According to John [8], the $\alpha + \beta$ is 0.999 implied that the volatility half-life is 694 days. It could be concluded that the volatility has a long memory which is persistent and mean-reverting [9]. The skewness for RIOT is 1.181442 which is negatively skewed, which may experience large gain and small losses.

3.2.5 Indian Energy Exchange - IEX

Table 3.9: IEX returns descriptive statistics from 2019-01-01 to 2021-01-01

DATA	505
MEAN	0.001112193
SKEWNESS	-0.6813687
KURTOSIS	6.69374
JARQUE-BERA	979.93 with P-value= 0.000000

Source: RStudio Analysis Output

Table 3.10 Result from the GARCH (1,1) for IEX

COEFFICIENT	COEFFICIENT FACTOR	STANDARD ERROR	P-VALUE
ω	0.000027	0.000012	0.021232
α	0.177816	0.049360	0.000315
β	0.718497	0.080730	0.000000
$\alpha + \beta$	0.896313	-	-
μ	0.001178	0.000604	0.050973

Source: RStudio Analysis Output

A total of 505 daily returns were studied for two years period between January 2019 and January 2021. The Jarque-Bera test value of 979.93 indicated significant departures from normality for the stock. The skewness coefficient of -0.6813687 indicated the distribution was negatively skewed, which are compensated with high future returns for higher volatility. According to John, [8], the $\alpha + \beta$ is 0.896313 implied that the volatility half-life is 8 days. It could be concluded that the volatility has a long memory which is persistent and mean-reverting. The skewness for IEX is -0.6813687 which is negatively skewed, which may experience large losses and small gains.

3.2.6 Kulicke and Soffa Industries Inc. - KLIC

MARKET CAP: $3.494B

Table 3.11: KLIC returns descriptive statistics from 2019-01-01 to 2021-01-01

DATA	505
MEAN	0.001323759
SKEWNESS	0.708262
KURTOSIS	10.03348
JARQUE-BERA	2156.2 with P-value= 0.000000

Source: RStudio Analysis Output

Table 3.12 Result from the GARCH (1,1) for KLIC

COEFFICIENT	COEFFICIENT FACTOR	STANDARD ERROR	P-VALUE
ω	0.000068	0.000031	0.027678
α	0.166765	0.050257	0.000906
β	0.743257	0.078236	0.000000
$\alpha + \beta$	0.910022	-	-
μ	0.001736	0.001039	0.094718

Source: RStudio Analysis Output

A total of 505 daily returns were studied for two years period between January 2019 and January 2021. The Jarque-Bera test value of 2156.2 indicated significant departures from normality for the stock. The statistics showed that the company had a positive return of about 0.001323759 (0.132%) per day. According to John, [8], the $\alpha + \beta$ is 0.910022 implied that the volatility half-life is 9 days. It could be concluded that the volatility has a very long memory which is persistent and mean-reverting. The skewness for KLIC is 0.708262 which is positively skewed, it expected to get small losses and large gains [11].

4. Conclusion

This study showed the level of volatility and tail risk presence in the stock market. It characterised the risk and return behaviour of the small-cap and big-cap companies. The presence of GARCH terms on each of the indices proved the presence of volatility. The α coefficient showed the effects of shocks in the earlier periods. Higher values implied that the effects of shocks in earlier periods tend to stay for a longer period than they did on other indices. This also implied less market efficiency than other indices as the time taken to return to normalcy was longer than the others. The β coefficient captured the long term influences on volatility. Higher values mean higher influence of the long term on volatility. This empirical study during this specific period might also differ significantly from the results of other studies. Overall the data analysis displayed similar characteristics for volatility and tail risk for both big-cap and small-cap companies except Riot Blockchain Inc., which has the longest volatility half-life and has the highest performance in small-cap companies. Apple Inc. has the longest half, 21 days, among the big-cap companies. Comparison in small-cap and big-cap companies, Riot Blockchain Inc. has the highest performance with 694 days compared with the highest volatility half-life 21 days of big-cap companies. The volatility half-life is the time taken for volatility to move halfway back from the unconditional mean after deviating from it. The volatility can present generate solid returns for shrewd investors. There can be an opportunity even when markets fluctuate, crash, or surge.

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