A Study on the Behaviour of NIFTY Sectoral Indices

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Preface

SDM Research Centre for Management Studies (SDM RCMS), since inception, has endeavoured to promote research in the field of business management in different ways. One of the initiatives undertaken, in this direction, was to enable Faculty to pursue applied research projects in the realm of management.

Broadly, an applied research project is expected to answer a specific question, determine why something is failed or succeeded, solve a specific and pragmatic problem relating to the business, economy, or policies. It may also intend to study the relationship and applicability of management theories or principles to the solution of a problem. It uses the data on a specific set of circumstances directly for real world application with the goal of relating the results to a situation. Hence an applied research is looked upon to develop strategic ways of addressing/solving the problems, thereby contribute with suggestions to the successful business and economy or effective policy implementation.

The Institute promotes such projects through the grant of funds and provision of needful research infrastructure. Generally, the applied research projects are completed in the duration of six to eight months and they could be in the form of case study, monograph, organisation/firm-based study, evaluation-based study of policy/scheme/institution or other types of studies/projects as deemed necessary by the Faculty, provided they fit into the broad nature of applied research.

It is heartening to note that the initiative has been effectively grabbed by the Faculty who are recruiting students as research assistants in the process of the projects. It has been found that this exercise enriches the knowledge of the students by extending their academic activities, outside the classroom learning situation, in the real world.

The project outcome is intended to help the firm concerned in fixing up the problem/addressing the given situation, and the Faculty to gain first-hand experience that enables in formulating hypotheses to get into a deeper research with wider scope. The findings from such practical exercises are disseminated to the wider world through FDPs, MDPs and publications. True to its objectives Faculty from SDMIMD are successful in harnessing the greater benefits of knowledge creation and its transfer from the applied research projects.

Dr.B.Venkatraja
Chairperson, SDM RCMS

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Executive Summary

Stock market prices/indices modeling is an age-old problem and many researchers have built various probability models to understand their behavior. One such model that was frequently used was the Normal probability model. Using this model chances of occurrence of a change in the prices/indices were measured and used for decision making. But during the years 1950-59, researchers found that the model fails due to high kurtosis (Lepto Kurtosis) and since then attempts are being made to find the right model that best fits the behavior of the price/index changes. In the process, researchers have found models like Log-normal, student-t, Pareto, Burr, etc. Few researchers have found that in a few cases stable models best fit the behavior. The deviation from normality is due to the presence of extreme prices/indices, which arise due to the presence of extreme events in the market. In cases where there is a deviation from normality, it is advised to study the tail behavior of the prices/indices and also the cumulative stock price/index variable. Measuring the tail index will help the decision-makers to identify the thickness of the tail and this will make the decision-makers realize the presence of extreme events. Studying this and identifying the periods where the tail is heavy, separately will help one to identify the events responsible for this behavior, and monitoring them in the future will help them to minimize the risk associated with these events. Sometimes, studying the cumulative price/index variable will also help one in identifying the extent of the influence the extremes have on the behavior. If the impact is higher then the probability model of the cumulative variable will be different from normality and this is identified through the stable index. Using these two aspects, one can completely identify the deviation from normality, and reasons for the same and appropriately chose other models that best suit the behavior. Not only the regular behavior of the price change but also sometimes decision makers will be interested in extreme (minimum or maximum) changes. In such cases, one can use extreme value theory for modeling the extreme changes. Studying this will help one estimate the extreme prices/index values.

We consider these three aspects, Estimating the tail index, Estimating the stable index, and Identifying the extreme value model, as the major objectives of the study.

We have considered the Nifty sectoral indices in the current study for the last 12 years (2010-2022) and studied their behavior. For each of the years, we estimate the tail index of the indices, estimate the stable index, and identify the extreme value distribution for the sectors.

We divide the report into the following sections. In the first section, we present the introduction to the NIFTY indexes, the tail behavior of a normal probability model, the importance of studying the tail behavior of a random variable, and other details about various tail behaviors (heavy-tailed, long-tailed, etc.). Also, to the extreme value distributions. In the second section, we present the literature review, followed by the need for the study and the objectives of the study. The fourth section gives the research methodology, followed by data analysis and results. We resent the discussion in section 6, followed by a framework for the practitioners. Finally, we present the conclusion and limitations.

To achieve the research objectives, we have adopted an exploratory research design. We considered each of the sectors and estimate the tail index, estimate stable index, and extreme index, for every year. Based on these index values, we classify the tail behavior of each of the sectoral indexes for every year, as heavy tail or normal tail. Similarly, classify the cumulative index variable for each sector, for every year either as stable or normal. Finally, estimate the extreme index to identify the extreme value distribution for all the sectoral indices. We also present the graphs for each of their behavior and present the changes in their behavior as time changes. Most of the tables and graphs are self-explanatory and we present a framework for the practitioners, who are analyzing the stock market indices.

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Introduction

Modelling the stock market prices/indices is an age-old problem and the normal model is the first choice to model the same. But the later studies have shown that normal model do not fit the movements appropriately (Mandelbrot (1963), Fama (1965)) and researchers have been working continuously to find alternative models. Among other models, log-normal distribution, Cauchy, Pareto, Burr models are being used as alternative models to a normal model. Even on a few occasions, these models turned out to be wrong and new models were built. Among several reasons, the drastic change in the tail behaviour of the stock index random variable is seen as an important reason. The heaviness/thickness of the tails are decided by the tail index value and based on the same, one can identify an appropriate model. For example, a normal model is used if the tail index value is 2 and a non-normal model if the tail index value is other than 2. One can use the properties of a normal model to under the behaviour of the stock index variable better.

The following gives the tail behaviour of a normal model.

$$P(Y > x) = \int_x^{\infty} f(x)dx \cong \frac{1}{x\sqrt{2\pi}} e^{-\frac{x^2}{2}} \quad (1)$$

The behaviour continues to be smooth and symmetric till the volatility or the variation of the random variable increases. Figure-1gives the structure of a normal distribution.

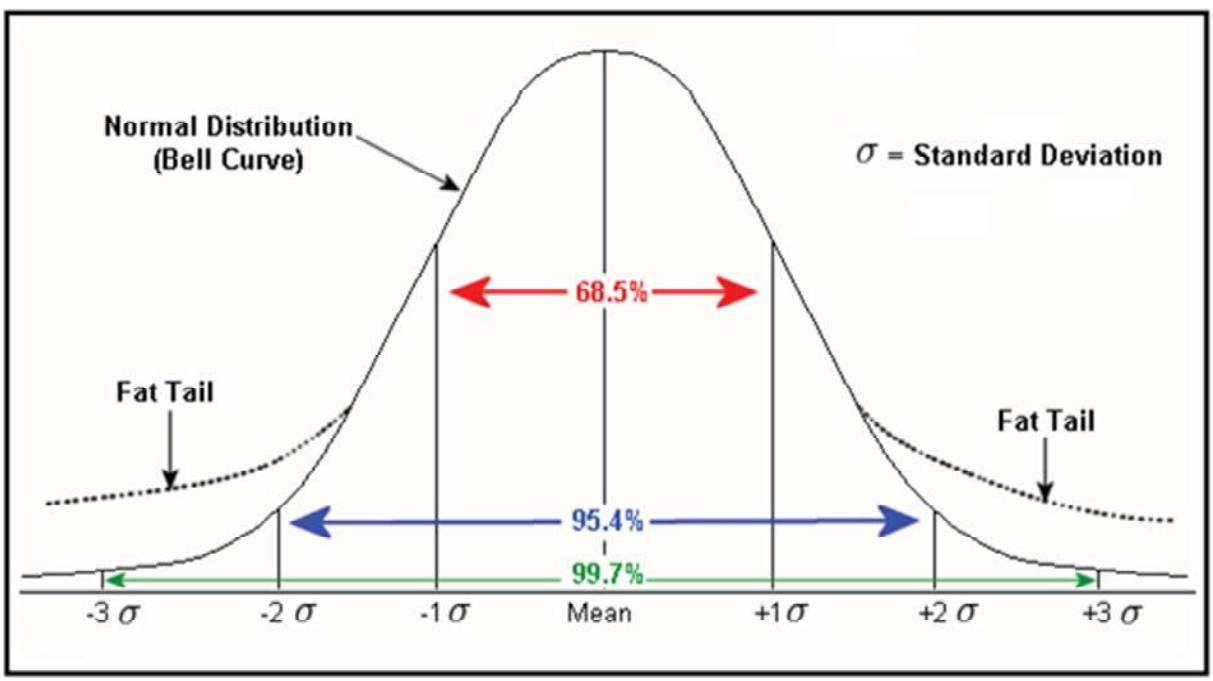


Figure 1 : Normal distribution tails and sigma limits

Source : https://www.clubstreetpost.com/2018/07/fat-tail-distributions-what-are-they-and-why-do-they-matter/

One can note that the tails of a normal law is are lighter than a stable law and becomes fatter as variance increases.

The behaviour of a random variable changes from normal to non-normal due to one of the following cases.

1. When the data is dominated by a large number of extreme values (either minimum or maximum), the variance increases, and high variance increases the skewness (kurtosis) value.

2. High-frequency values increase the kurtosis and lead to the failure of a normal model.

3. The presence of heavy tails also leads to the failure of a normal model. A heavy tail implies that there is a large probability of getting very large values.

When a normal model fails, one can use alternative models such as log-normal, Pareto, Burr etc. Fama (1963) shows that a stable Pareto model fits the stock price changes. Tails other than normal tails can be classified as heavy tails, fat tails, thin tails, etc.

Note that, a random variable's movement gets affected due to the existence of extreme values or outliers. The presence of a large number of extreme values increases the variance of the random variable and changes the symmetric behaviour of the random variable. Also, the kurtosis of the random variable increases with the presence of high-frequency data. Hence, the normal behaviour of a random variable gets affected due to the presence of extreme values. Hence, one has to note this and carefully identify a probability model that can explain the behaviour of the random variable properly.

The tail behaviour of the stock index random variable may change due to the change in the events. In a normal scenario, the tails will be symmetric, and one can easily study the behaviour of the random variable. When the tails become heavy none of the probability models can best fit the stock prices. This situation can arise only if the events are severe are change the stock prices drastically. Hence, we try to estimate the tail index value for each of the indices and classify the index. This forms one of the objectives of the current study.

When studying the behaviour of the sectoral indices, one may be interested in extreme stock index variables. For example, maximum index variable or minimum index variable. Hence, it is important to study and identify the probability model that best fits the maximum or minimum index random variable. This will help the practitioners to easily compute the probability of these variables crossing a given threshold and take decisions on the sectoral stock appropriately. For example, if the chances are high that the maximum index variable crosses a given threshold, then one can invest in that stock to other stocks. Similarly, avoid investing if the chances are low. This is the second objective of the current study.

In the current study, we also estimate the stable index, to check if the indices deviate from the normal behaviour and tend towards a stable behaviour. One can note that when a change in the index happens, it is due to the information generated and sometimes the individual information impacts the index such that it changes its behaviour drastically. In such cases to understand the capacity of the index to sustain to the information, one can study the cumulative index variable, The cumulative index variable is

generated as a sum of all the index values, that is, sum of the results of the information generated. If a piece or pieces of information generated impacts the index drastically, then the behaviour of the cumulative index changes from normality to a stable model. If the impact of the information generated is not that high, then it gets neutralized with the other complementary information generated against it. In such cases, the cumulative index variable tends to a normal model. In all other cases where the impact is very high, a stable model turns out to be an appropriate model. We study the behaviour of the cumulative index for all the sectoral indexes and identify the sectors and the year in which the model deviated from normal to stable. This forms the third objective of the study.

In the following sections, we introduce the extreme value distributions, stable distributions and present the discussion on the tail behaviour of a random variable. We also present the details of NSE in brief and the list of sectoral indices considered in the current study.

Tail Behaviour of a random variable and its importance

In this section, the discussion on tail behaviour of a random variable and its importance.

It is well known that the behaviour of a random variable can be explained based on the tail behaviour of its probability distribution. When the tails are non-normal, one has to study and find the model that best fits the pattern of the random variable under consideration. The tails of a random variable are highly influenced by the presence of extremes and lose their normal behaviour. In such cases, the tail behaviour is classified as heavy-tailed, fat-tailed or with a sub-exponential tail. Also, the moments of a random variable are directly linked with the tail of the random variable. In a few cases, the mean or other moments do not exist, because of heavy tails.

For any random variable X, the distribution function is given by

$$F(x) = P(X \leq x), \qquad x\, real.$$

Then, the tail probability is given by

$$1 - F(x) = P(X \geq x)$$

The relation between the tail probability and the expected value is given by

$$E(X) = \int_0^\infty P(X > x)dx$$

One can note that if the tail is heavy, then the expected value or the mean value gets affected. For example, the expected value doesn't exist for a Cauchy random variable.

Heavy tailed distribution

A random variable is said to have a heavy tail if the moment generating function of X, $M_X(t)$, is infinite for all t > 0. That is,

$$\int_{-\infty}^{\infty} e^{tx}\, dF(x) = \infty \quad \text{for all } t > 0.$$

The same can be expressed in terms of the tail distribution function

$$\overline{F}(x) \equiv \Pr[X > x]$$

$$\lim_{x\to\infty} e^{tx}\overline{F}(x) = \infty \quad \text{for all } t > 0.$$

It is a usual practice to use exponential distribution as a reference for measuring the mass in the tail of a probability density function. The PDF of the exponential distribution approaches zero exponentially fast. That is, the PDF looks like exp(-λx) for large values of x. Thus, the distributions can be divided into two categories

according to the behaviour of their PDFs for large values of $|x|$.

- The thin-tailed distributions are class of that decay faster than an exponential and normal distribution is an example of a thin-tailed distribution, whose PDF decreases like exp $(-x^2/2)$ for large values of $|x|$. A thin-tailed distribution does not have much mass in the tail, so it serves as a model for situations in which extreme events are unlikely to occur.

- Probability distribution functions that decay slower than an exponential, are called *heavy-tailed distributions*. An example of a heavy-tailed distribution is the *t* distribution. The tails of many heavy-tailed distributions follow a power law (like $|x|^{-\delta}$) for large values of $|x|$. A heavy-tailed distribution has a substantial mass in the tail, so it serves as a model for situations in which extreme events occur somewhat frequently.

Fat-tailed distributions

A probability distribution that exhibits a large skewness or kurtosis, in comparison to either a normal distribution or an exponential distribution is called a fat-tailed distribution. The tails of Fat-tailed distributions decay like a power law.

$$\Pr[X > x] \sim x^{-\alpha} \text{ as } x \to \infty, \qquad \alpha > 0.$$

Here, α is small. For example, $\alpha<3$ the variance and skewness of the tail is mathematically undefined and hence larger than normal or exponential distribution.

Long-tailed distribution

A random variable X is said to have a long-tailed distribution if it has the distribution function F such that, if for all $t>0$

$$\lim_{x\to\infty} \Pr[X > x+t \mid X > x] = 1,$$

or

$$\overline{F}(x+t) \sim \overline{F}(x) \quad \text{as } x \to \infty.$$

One can observe that all long-tailed distributions are heavy-tailed, but the converse is not true.

Sub-exponential distributions

A distribution function with support is a sub-exponential distribution, if for all $n \geq 2$

$$\lim_{x\to\infty} \frac{\overline{F^{n*}}(x)}{\overline{F}(x)} = n.$$

Tail behaviour for the generalized extreme value distribution

The tail of the generalized extreme value distribution is given by

$$P(X > x) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{\frac{-1}{\xi}}\right\}, \text{ for } 1+\xi\left(\frac{x-\mu}{\sigma}\right) > 0 \text{ and } \xi \neq 0$$

The extreme of a random variable is classified into one of the three extreme value distributions, based on the value of î.

Tail Behaviour of stable distributions

We now present the details related to the tail behaviour of stable distributions.

The tail of a stable random variable with an index between $0 < \alpha < 2$ is given by

$$\begin{cases} \lim_{\lambda\to\infty} \lambda^\alpha P\{X > \lambda\} & = C_\alpha \frac{1+\beta}{2}\sigma^\alpha, \\ \lim_{\lambda\to\infty} \lambda^\alpha P\{X < -\lambda\} & = C_\alpha \frac{1-\beta}{2}\sigma^\alpha, \end{cases}$$

where,

$$C_\alpha = \left(\int_0^\infty x^{-\alpha}\sin x dx\right)^{-1} = \begin{cases} \frac{1-\alpha}{\Gamma(2-\alpha)\cos(\pi\alpha/2)} & \text{if } \alpha \neq 1, \\ 2/\pi & \text{if } \alpha = 1. \end{cases}$$

If the index value α is equal to 2, then the model is normal and if the value is less than 2 then, the model is stable.

The following gives the existence of moments for the value of alpha.

- $1 \leq \alpha < 2$, all moments diverge, ie. $E(X) = \infty$
- $2 < \alpha \leq 3$ all second and higher – order moments diverge, ie. $E(X^2) = \infty$
- $3 < \alpha \leq m + 1$, all m and higher – order moments diverge, ie. $E(X^m) = \infty$
- All moments are finite when the distribution is normal.

If the tail index has a value less than 1 or between 1 and 2, then it is classified as heavy-tailed, and moments of any order does not exist.

If the tail index has a value between 2 and 3, then it is classified as heavy-tailed and only mean exists.

If the tail index has a value between 3 and m+1, then it is classified as heavy-tailed, and mean and variance both exists.

If the tail index is equal to 2, then the tails are normal, and all the moments exist.

Introduction to Extreme Value Theory

In this section, we present the details related to extreme value distributions and the corresponding classification based on the tail index value.

Extreme value distributions arise as limit distributions of the maximum or minimum on 'n' independent and identically distributed random variables. The commonly used distributions are Gumbel (type-1), Fréchet (type-2), and Weibull (type-3). The type of distribution is decided based on the extremal index value. The discussion on these limiting distributions dates to papers by Fréchet (1927), Fisher and Tippet (1928), von Mises (1936), and Gnedenko (1943). de Haan (1970) proposes the domains of attraction of the extreme, usually called max-stable or min-stable laws. Any type has three parameters- location, scale and shape. Also, each type has support and the corresponding characteristics. Note that, each type has other distributions getting attracted and the set of distributions form the domain of attraction of that type. Also, that irrespective of the original distribution, one can study the behaviour of the extreme random variables. We now present details of each type separately. The following gives the three types of extreme value distributions.

Type 1 : Gumbel type or domain

The following is the distribution function of a Gumbel law.

$$F(x;\mu,\sigma,0) = e^{-e^{(x-\mu)/\sigma}}, for\ x \in R$$

Note that, the first type has the extremal index value is at level zero and one can classify the distribution of the extremes as Gumbel if the index value is close to zero. The index value can be estimated using one of the methods like Hill estimator or Pickand's estimator etc (refer to section-for further details).

Type 2 : Fréchet law of domain

The following is the distribution function of a Fréchet law.

$$F(x;\mu,\sigma,\xi) = e^{-y^{-\alpha}}, y \geq 0$$

Here $\xi = \frac{1}{\alpha} > 0$ and $y = 1 + \xi(x-\mu)/\sigma$ If, $\xi > 0$ then we classify the corresponding distribution under Fréchet law. Using the data collected on the original random variable, we estimate the index and based on the value we classify the distribution of the maximum random variable.

Type-3: Weibull law of domain

The following is the distribution function of the Weibull law

$F(x;\mu,\sigma,\xi) = e^{-(-y)^{\alpha}}, y < 0 \; and = 1, y \geq 0.$

Here $\xi = -\frac{1}{\alpha} < 0$ and $y = -(1 + \xi(x-\mu)/\sigma)$.

If $\xi < 0$ then we classify the corresponding distribution under a Weibull law.

Generalized Extreme Value Distribution

The three types of distributions can be represented using generalized extreme value (GEV) distribution. The following is the distribution function of the GEV

$$F(s;\xi) = \begin{cases} \exp(-(1+\xi s)^{-1/\xi}) & \xi \neq 0 \\ \exp(-\exp(-s)) & \xi = 0 \end{cases}$$

where $\xi \in R$ is the shape parameter, $S = (x - \mu) / \sigma$, where is the $\mu \in R$ location parameter, and $\sigma > 0$ is the scale parameter.

Based on the value of the shape parameter, the three types of extreme value distributions can be represented. If the value of $\xi = 0$, then one gets a Gumbel law. If the value of , then one gets a Fréchet law. If the value of $\xi < 0$, then one gets a Weibull law.

In the current study, we compute the value of ξ for each of the sectoral indices and based on the value of ξ the distribution of the maximum and minimum index price random variable will be classified. Note that, the distribution of minimum is obtained by considering the negative of the random variable considered. That is, -X is substituted in the place of X to obtain the distribution of minimum stock price random variable.

Introduction to Stable distributions

The limiting distributions of sums of random variables are the stable distributions and used in modelling the behaviour of the cumulative stock price or index.

It is well known that there exist two situations while studying the behaviour of the random variables. In the first case, the variance of the random variable is finite and in the second case, the random variable has an infinite variance. In either of the cases, the behaviour of the random variable can be modelled using an appropriate probability model. Stable distributions are used to model the random variables with infinite variance. In the case of finite variance, a normal model is used. The appropriate model is identified using the estimate of the tail index. If the tail index value is equal to 2, then the model is normal. If the index value is less than 2, then the model is stable. If the index value is equal to 1, then the model is Cauchy and if the value is 0.5, then the model is Levy. Note that, larger variance implies heavy tails.

Stable distributions are characterized by four parameters- tail index or exponent ($\alpha \in [0, 2]$), skewness parameter ($\beta \in [-1, 1]$), scale parameter ($\sigma > 0$), and location parameter ($\mu \in R$). The tail index decides the rate at which the tails of the distribution taper off. When $\alpha = 2$, the resulting distribution is normal. When $\alpha < 2$, the resulting distribution has variance as high as infinity and the tails are asymptotically equivalent to a Pareto law. When $\alpha > 2$, stable distributions exhibit a crossover from a power decay to the true tail with exponent α. When $\alpha > 1$, then the mean of the distribution exists and is equal to μ. The moments do not exist if $\alpha < 1$. If $\beta > 0$, then the distribution is positively skewed (the right tail is thicker) and negatively skewed if $\beta < 0$. When $\beta = 0$, one gets symmetric stable distribution. As α approaches 2, β loses its effect and the resulting distribution is a Gaussian distribution. The other two parameters

μ and σ are respectively the location and the scale parameters. While σ determines the width, μ determines the shift of the mode. When $\mu = 0$ and $\sigma = 0$, one gets a standard stable distribution.

Introduction to NSE

National stock exchange (NSE) is the leading stock exchange in India, located in Mumbai. It was established in 1992 and was the first dematerialized electronic exchange in the country. It was the first exchange in the country to provide a modern, fully automated screen-based electronic trading system. Mr Vikram Limaye is the Managing Director and Chief Executive officer of NSE.

NSE has a total market capitalization of more than US$2.27 trillion and is the 11th largest stock exchange as of April 2018. NIFTY 50, the 50-stock index if the flagship index of NSE and is used extensively by investors in India and abroad. This index was launched in the year 1996 and acts as a barometer of the Indian capital markets. In India, stock trading in BSE and NSE account for 4% of the economy and the major portion is derived from the unorganized sector and households. The corporate sector in India accounts for 12-14% of the national GDP and 7,800 companies are listed, out of which 4000 trade on BSE and NSE. According to economic times news on April 2018, 60 million retail investors have invested in stocks in India. These investors invest either through direct purchases of equities or through mutual funds. In USA 27% of the population had invested in the stock market, in China it is 10%, and in India it is 1.3%.

NSE offers trading and investment Equity, derivatives, and debt segments. Trading on equity segment takes place on all days of the week, except Saturdays, Sundays and holidays declared by the exchange in advance). The market timings of the equity segment are

Pre-open session:

- Order entry and modification Open: 09:00 hrs
- Order entry and modification Close: 09:08 hrs*

*with random closure in last one minute. Pre-open order matching starts immediately after the close of pre-open order entry.

Regular trading session

- Normal/Retail Debt/Limited Physical Market Open: 09.15 hrs
- Normal/Retail Debt/Limited Physical Market Close: 15:30 hrs.

NSE's trading systems is a state-of-the-art application. It has an uptime record of 99.99% and processes more than a billion messages every day with the sub-millisecond response time.

NSE has taken huge strides in technology in these 20 years. In 1994, when trading started, NSE technology was handling 2 orders a second. This increased to 60 orders a second in 2001. Today NSE can handle 1,60,000 orders/messages per second, with infinite ability to scale up at short notice on demand, NSE has continuously worked towards ensuring that the settlement cycle comes down. Settlements have always been handled smoothly. The settlement cycle has been reduced from T+3 to T+2/T+1.

(The information on NSE is taken from https://en.wikipedia.org/wiki/National_ Stock_ Exchange_ of_ India)

Sectoral Indices considered in the study

Table 1 : Sectoral Indices Considered

Sl. No.	Index Name
1	NIFTY Auto Index
2	NIFTYBank Index
3	NIFTY Financial Services Index
4	NIFTY Financial Services 25/50 Index
5	Nifty Financial Services Ex Bank
6	NIFTY FMCG Index
7	NIFTY Healthcare Index
8	NIFTY IT Index
9	NIFTY Media Index
10	NIFTY Metal Index
11	NIFTY Pharma Index
12	NIFTY Private Bank Index
13	NIFTY PSU Bank Index
14	NIFTY Realty Index
15	NIFTY Consumer Durables Index
16	NIFTY Oil and Gas Index

Source: https://www.niftyindices.com/indices/equity/sectoral-indices

Literature Review

Mandelbrot (1963) studies the behaviour of the stock returns and points out that the returns do not follow a normal model and suggests that a stable-Paretian will be an appropriate model to study the behaviour of returns. Note that, when the kurtosis or skewness increases there is every possibility for the variance to increase and sometimes can reach infinity Here, one can question the validity of the statistical methods that depend on the assumption of the finite variance. Fama (1965) states that statistical methods developed based on the assumption of finite variance do not work if the variance of the distribution of returns is large. He considers testing of the hypothesis of Mandelbrot for the case of stock prices. At this stage, one can question of alternative models. Hsu, Miller and Wichern (1974) propose an alternative model to study the rates of return based on the hypothesized phenomenon of a changing variance. In cases where the variance increases one has to investigate the tail behaviour of the random variable. Akgiray and Booth (1988) investigate the tail shapes of empirical distributions of returns on an extensive group of common stocks. Their study finds that the returns distributions have tails thinner than an infinite variance stable distribution. They also argue that economic and statistical inferences drawn from stable-law parameters estimated from samples of stock returns may be misleading. In such cases, one tends to look for normal distribution or a better alternative. Gray and French (1990) examine the ability of the normal distribution to model log price returns from the S&P 500 composite index and compare its performance to three alternative finite variance distributions (scaled- distribution, logistic distribution, and exponential power distribution). It is a known fact that the variance of any random variable increases due to the presence of extremes. But sometimes, the aggregate of the data points may neutralize the impact of these extremes. Also, large samples may decrease the variance. Hing-Ling Lau et.al. (1990) presents an effective procedure for determining whether a reasonably large sample comes from a stable population against the alternative that it comes from a population with finite higher moments. This procedure shows convincingly that stock returns, when taken as a group, do not come from stable populations. Even for individual stocks, their results show that the Stable-population- model null hypothesis can be rejected for more than 95% of the stocks. Tucker (1992) investigates the general (asymmetric) stable Paretian distribution and three finite-variance, time-independent distributions applied to daily

stock-return series. The study shows that finite time-independent models outperform the asymmetric stable Paretian distribution. Mittnik and Rachev (1993) show that a Weibull model associated with both the non-random- minimum and geometric-random summation schemes dominates the other stable distributions considered including the stable Paretian model. Peir (1994) suggests the use of Student's t-distribution to any other finite variance distributions including the normal distribution. Dillen and Stoltz (1999) show that the market returns have a Leptokurtic distribution, and their results suggest that much of the Leptokurtic can be attributed to a jump component in the distribution. Qi-Man Shao et.al. (2001) proposed a test statistic to discriminate between models with finite variance and models with infinite variance. Aparicio and Estrada (2001) consider daily stock returns of 13 European securities markets and shows that normality may be a plausible assumption for monthly (but not for daily) stock returns. Hoechstetter, Rachev and Fabozzi (2005) analyse the returns of stocks comprising the German stock index DAX concerning the stable distributions and shows that the stable hypothesis cannot be rejected. They also show that stable distribution outperforms the skew t-distribution. Xu Weidong et.al. (2011) demonstrate that a stable distribution is better fitted to Chinese stock return data in the Shanghai Composite Index and the Shenzhen Component Index than the classical Black–Scholes model. Ma and Serota (2014) prove that student-t distribution provides a better fit to returns of S&P component stocks and generalized inverse gamma distribution best fits VIX and VXO volatility data. Further, the study proves that stock returns are best fit by the product distribution of the generalized inverse gamma and normal distributions. Gnay (2015) checks whether daily returns of Brent crude oil, dollar/yen foreign exchange, Dow&Jones Industrial Average Index and 12-month libor display power-law features in the scaling exponent and probability distributions or not, using different methods. They show that the Brent crude oil and 12-month libor have a high persistency in the returns, while the dollar/yen foreign exchange and Dow&Jones Industrial Average Index returns have a short memory. According to the alpha-stable parameter estimations, all of the return series have thicker tails than a normal distribution. Corlu et. al (2016) investigates the ability of five alternative distributions to represent the behaviour of daily equity index returns over the period 1979–2014: the skewed Student-t distribution, the generalized lambda distribution, the Johnson system of distributions, the normal inverse Gaussian distribution, and the g-and-h distribution. They found that the generalized lambda distribution is a prominent alternative for modelling the behaviour of daily equity index returns. Naumoski et.al. (2017) rejects through empirical evidence that equity returns do not follow a normal distribution. They consider the stock returns of southeast European emerging markets and show that stock returns are leptokurtic with negative skewness. The study shows that the Johnson SU distribution best fits the daily returns and for weekly and monthly returns, there is no one predominant distribution that can best fit the stock returns.

Afuecheta et.al. (2018) proposes three models based on scale mixing of the Student's t distribution and shows that they better fit than some known generalizations of the Student's t distribution, including those having more parameters.

In recent times, researchers have attempted to study the stylized facts about the Indian stock market. Sen and Manavathi (2019) study the

stylized facts about the Indian stock market. One important observation they make is, as the time scale over which returns are calculated increases, then the distribution looks normal. They consider the 50 stocks listed under NIFTY and finds that fewer stocks are non-normal. P-values are less and less concentrated around zero and many stocks become similar to normal as time over which returns are calculated is lengthened.

We now present the studies that have adopted extreme value theory in the analysis of the stock market data.

The studies of Longin (1996), Jondeau and Rockinger (2003), Tolikas and Gettinby (2009) have indicated that the assumption of normality may lead to underestimation of risk. Normal distribution may not be the right choice to model extreme stock returns. Extreme value theory (EVT) focuses on modelling the extreme returns and helps one to identify the distribution that best fits the behaviour of the extreme returns. EVT is used to model the stock returns by specifically focusing on the tails. Parkinson (1980) states that the tail of the empirical distribution contains important information for the variance of the returns. EVT is also used in the calculation of value at risk (VAR). Longin (2000) presents the application of EVT in the calculation of VAR of a fully aggregated position and multivariate EVT in the calculation of VAR of a position decomposed on risk factors. Ho et.al. (2000) measures VAR using EVT by modelling the tails of the return distribution of six Asian financial markets. They show that the maxima and minima were appropriately modelled using EVT as compared to other traditional methods, especially for markets (Malaysia and Indonesia) for which the Leptokurtosis is high. Gencay et.al. (2003) uses EVT in VAR calculations and compare the performance with other well-known modelling techniques such as GARCH, variance-covariance method, and historical simulation. The study shows that generalized Pareto distribution (GPD) is a robust model in the calculation of VAR. Carvalhal et.al. (2003) use EVT to analyse 10 Asian stock markets for identifying the type of extreme value distribution that better fits historical extreme value events. They show that normal distribution is not an appropriate distribution under the influence of extreme market events and maxim and minima were modelled using EVT. Also, show that VAR calculated using EVT was a more conservative method than the traditional methods. Byström (2004) apply unconditional and conditional EVT models to the management of extreme risks in stock markets. The study finds that the conditional EVT model gives accurate VAR values and as compared to GARCH models the VAR calculated using EVT models were superior. Longin (2004) shows that EVT will be useful to study the behaviour of the asset returns and for understanding the characteristics of the distribution of the asset returns. This is true when the real financial data exhibit extreme price changes such as stock market crashes, which assumes normality to fail. Gilli and Evis (2006) use EVT for measuring the risk while handling rare and extreme events. Cumperayot et.al. (2006) investigate the link between extreme events and stock markets for 26 countries by estimating a simultaneous equations probit model. They use a sample of 2500 daily returns for the period between 1996 and 2005. They show that, for currency markets, there exists evidence of spillover of extreme events within regions and less influence outside the region. They claim that extreme events were interrelated globally when originated from the US. Wentzel and Mare (2007) show that EVT fits the returns of the South African

equity market and normal distribution do not fit the returns. Straetmans et.al. (2008) apply EVT to US sectoral indices to assess if the tail risk were significantly altered by 9/11. Considering 9/11 as the midpoint, the authors find that tails often increase in a statistically and economically significant way. Assaf (2009) use EVT to analyze the four emerging markets belonging to the MENA region. The study provides an estimate of the tails of the unconditional distribution of the returns and shows that the tails are significantly fatter than the normal distribution. Then compute the maximum daily loss by calculating the VAR in each of the markets. Kourouma et.al. (2010) use Peak over Threshold (POT) and generalized Pareto distribution of EVT to measure VAR and expected shortfall for CAC 40 and S&P 500 indexes during the 2008 financial crisis. They consider 1 day, 5 days and 10 days, time horizons. The results obtained using EVT are compared with the traditional simulation through the backtesting process on 250 days. They show an underestimation of the risk of loss for VAR models and this underestimation is stronger for the historical VAR model than the EVT VAR model. Anðeliæ et.al. (2010) investigates the performance of EVT on the daily stock returns of four emerging markets and attempts to estimate the tails of daily return distribution of the analyzed stock indexes. Singh et.al. (2013) consider ASX-All Ordinaries (Australian index) and the S&P-500 (USA) index and apply univariate extreme value theory to model the extreme market risk. They demonstrate that VAR, CVAR, expected return level and daily VAR can be successfully calculated using EVT. The Studies of Cotter (2007), Marimoutou et.al. (2009), Allen et.al. (2013), and Karmakar (2013) reveal that extreme stock returns in the US can be characterized by the generalized extreme value (GEV) distribution and can be used for calculating VaR measures and capital requirements. Generalized Logistic distribution and Generalized extreme value distributions are used frequently to study the behaviour of extreme returns. The study by Gettinby et al. (2004 and 2006) shows that Generalized Logistic (GL) distribution fits extreme daily returns better than the Generalized extreme value (GEV) distribution. Tolikas and Gettinby (2009) show that GL distribution is the best fit for the distribution of extreme daily share returns in Singapore. Hussain and Li (2015) study the distribution of the extreme daily returns of the Shanghai Stock Exchange (SSE) composite index. Their results suggest that Generalized Logistic (GL) is a better fit for the minima series and the Generalized extreme value (GEV) is a distribution for the maxima series. Gabriel (2017) considers the Peruvian stock market returns and uses EVT to model the daily loss probability, estimates the maximum quantiles and tail probabilities of the distribution and models extremes through a maximum threshold. The same is used to measure value at risk (VAR) and expected shortfall (ES). They show that Gumbel and Fréchet fit the extreme returns and Generalized Pareto distribution (GPD) in comparison with normal distribution, giving better estimates for VAR and ES. Louangrath (2016) use EVT to review three models: modern portfolio theory, Black-Scholes, and Jarrow-Rudd models. The study uses the daily close price from a period of 30 days from 100 companies in the SET 100 Index. They calculate the tail index and based on the same they classify each of the securities. The study found that Weibull distribution was the right choice for a majority of the stocks and the remaining Fréchet distribution was the choice. Empirically they show that stocks from different sectors have the same distribution and stocks from the same sector have different distributions.

While modelling the returns, in cases where the tails become heavy due to extremes, it is suggested to use stable distributions to model the behaviour of the stock markets. In such cases, the tails become heavy and use stable models (Fama (1965), Mandelbrot (1963)). Other studies that argue on the use of the stable model in the stock market and financial applications include Akgiray and Booth (1988), Tucker (1992), Mittnik and Rachev (1993), Anna (1996), McCulloch (1996), Hoechstetter et.al. (2005), Belov (2006), Xu Weidong et.al. (2011), Borak et.al (2011), Gûnay (2015), Baþeðmez (2017), Bielinskyi (2019). Nolan (2014) gives an extensive discussion on the use of stable distributions in modelling the stock market returns.

From the above literature review, one can note that not many studies have been taken up on the NIFTY indices and the current study fills the gap.

Need for the current study and objectives of the study

As indicated earlier, to date attempts are being made to find the best model that fits the stock market movements. The usual process is to use a test procedure to check if the model chosen best fits the movements. But most of the test procedures are developed with assumptions and sometimes these assumptions are not satisfied by the data and relying on the results of such procedures will be misleading. Also, those procedures for which the assumptions are satisfied may have less power in testing the hypothesis related to the model fit. Hence, it is advised to decide on the model based on the tail behaviour of the random variable. To achieve this, one has to estimate the tail index using the data collected on the random variable and use the same to estimate the tail index. Based on the value of the index, one can check if the normal or other models suit the behaviour. Also, while studying the stock market behaviour, the traditional approach is to use the methods under time series analysis and build the forecasting models. These studies are on either stock returns or volatility modelling or original stock prices. Few studies also were on NIFT indices, stocks etc. Not many attempts are made on studying the behaviour of the individual sectoral indices.

Another aspect that motivated us to consider the study is the behaviour of the extremes. Not many studies attempted to build the models for the minimum and maximum index variables. This is necessary if one is interested to check if the minimum index value crosses a given threshold and computing the corresponding probability. Similarly, if one is interested in computing the probability of the maximum index variable crossing a given threshold. In both cases, one has to use extreme value theory. To identify the model from the available extreme value models, one has to estimate the extremal index and identify the corresponding model. The data collected has to be used to estimate the index value and decision to be taken based on the same. Not many have attempted to study the behaviour of extreme NIFTY sectoral indices.

The third aspect is to identify the thickness of the tails of the stock market index variables and understand the domain the cumulative index variable belongs to. This will help those who are interested to compute the probability of the cumulative index variable crossing a given threshold. This is because the goal is to aggregate the values and make the decision based on the results of the aggregation. In such cases studying the cumulative index variable's behaviour will be useful for the decision-makers. The domain the cumulative index variable belongs to can be

identified by measuring the thickness of the sable index. This process will help one to classify the domain as either normal or stable. If the domain is normal, then one can use the properties of the normal model to understand the behaviour of the cumulative variable completely. If the domain is stable, then appropriately the cumulative variable can be studied using stable densities. The important point here is, if the domain is stable, then one can also conclude that the events happening around the index have a high impact on the index. This is because it increases the heaviness at the tails. In a way, this process will help one to check if the volatility is high or not and at the same time whether the events around the index have an impact or not. Not many have attempted to study the behaviour of the cumulative measure of the thickness of the tails for the NIFTY sectoral indices. The interesting point here is, under this, the cumulative index variable will be studied rather than the individual variable's behaviour. In a way, this will help to neutralize the contribution from the individual index values and consider only the aggregate of the values. The advantage is one can use the normal model to study the behaviour of the cumulative index variable.

Taking the above into consideration, we have the following three objectives of the study.

1. To estimate the tail index for each of the NIFTY sectoral indices and identity the model that suits the behaviour of the indices.

2. To identify the extreme domain for the minimum and maximum indices for each of the sectoral indices.

3. To measure the thickness of the tails and classify the cumulative indices to either normal or stable.

Research Methodology

Research Design

To achieve the objectives of the study, a descriptive research design was adopted.

One uses a descriptive research design if the interest is to describe the characteristics of the population considered. The "What" "How", and "When" questions are answered under this design. Under this, one studies the characteristics of the population looks at describing the given situation or the population, using descriptive categories. It helps one to understand the current status through the process of data collection, which enables one to describe the situation completely. It is an appropriate choice if one is interested in identifying the characteristics, frequencies, and trends.

The main objective of the current research is to describe the changes in the pattern of the NIFTY sectoral indices, with changes in the time points. That is, note the changes in the tail behaviour, distribution of extremes, probability model that suits the behaviour of sectoral indices. Hence to achieve these, we chose a descriptive research design.

Data and the time horizon

The data required to meet the objectives of the study are the daily closing indices and the same is collected from the NSE website. The time horizon considered was ten years, starting from 2010 to 2022. We study the behaviour of the indices for every year and note the change with the change in time.

Methods used for estimating the tail index

In this section, we present the details of the methods used for estimating the tail index, the

process of identifying the extreme behaviour, and identifying the probability structure of the sectoral indices.

1. The tail index for each of the sectoral indices is estimated using the weighted least squares estimator proposed by Nair et.al. (2019). Here the weight Wi and tail index are given by

$$w_i = \left[\ln\left(\frac{x_i}{\hat{x}_{\min}}\right)\right]^{-1}$$

$$\hat{\alpha} = \frac{-\sum_{i=1}^{N} \ln\left(\hat{y}_i/N\right)}{\sum_{i=1}^{N} \ln\left(x_i/\hat{x}_{\min}\right)}$$

where Xi is the data point for i = 1, . . . , N, The minimum value, $X\ min$ is estimated from the data set and hence denoted $\hat{x}_{min}$. For each value, i (of N data points) γi is the number of points greater than the ith data point. We use the package "ptsuite" available in R for calculation purposes.

2. The tail index for the extreme value distributions is estimated using the generalized extreme value distribution. For each of the sectors, the generalized extreme value distribution will be fit and based on the index value calculated, we identify the distribution that best fits the behaviour of maximum and minimum index variables. The cumulative distribution function (CDF) of GEV distribution is the following

$$F(s;\xi) = \begin{cases} \exp(-(1+\xi s)^{-1/\xi}) & \xi \neq 0 \\ \exp(-\exp(-s)) & \xi = 0 \end{cases}$$

and the corresponding density function is given by

$$f(s;\xi) = \begin{cases} (1+\xi s)^{(-1/\xi)-1} \exp(-(1+\xi s)^{-1/\xi}) & \xi \neq 0 \\ \exp(-s)\exp(-\exp(-s)) & \xi = 0 \end{cases}$$

R package "evd" is used to fit the generalized extreme value distribution. The distribution is identified as Gumbel if the value of ξ=0 or close to 0, as Fréchet if the value of ξ>0, and Weibull if the value of ξ<0.

3. Koutrouvelis (1980) method is used to estimate the stable index or exponent. We use the package "libstableR" to estimate the stable index or exponent and use the function stable_fit_koutrouvelis (), which implements Koutrouvellis' method based on the characteristic function. If the index value is 2, then the probability model that suits the behaviour of an index is normal and stable, if the index value is less than 2.

Data Analysis and Results

In this chapter, we present the data analysis and the model-building process adopted, to meet the objectives of the study. We first present the descriptive statistics for all the indices considered in the study, followed by the results for tail behaviour, extremes and the cumulative index variable.

We attempt to check if the normal model best fits the indices for each of the years, and based on the same, study the tail behaviour of the indices. Tail index for each of the indices will be computed and presented separately. Based on the tail index value, the behaviour of the indices will be classified as heavy/thin tailed. If the tails are found to be heavy, then we attempt to fit the stable/ tempered stable models. This process will help one to understand how the behaviour of the indices changes with the change in time (that is, year), and this will help one to further investigate the impact of individual events or news on the indices during these time horizons. The current study mainly focuses on identifying the change in the models with the

change in the time. We consider the indices from 2010 to 2022, that is after the financial crisis. This is just to observe the behaviour after the crisis and one can also adopt the procedure proposed in this study for other periods as well.

Results of the Analysis for the Sectoral Indices

In the first part, we present the tables that give the descriptive statistics and the results of the test of normality of the indices, year-wise. In the second part, we present the tail index and the model that can best fit the index behaviour, a table that gives the model for the minimum and maximum, a table that gives the stable tail index value. We also present the overall conclusion at the end of the index.

NIFTY AUTO Indices

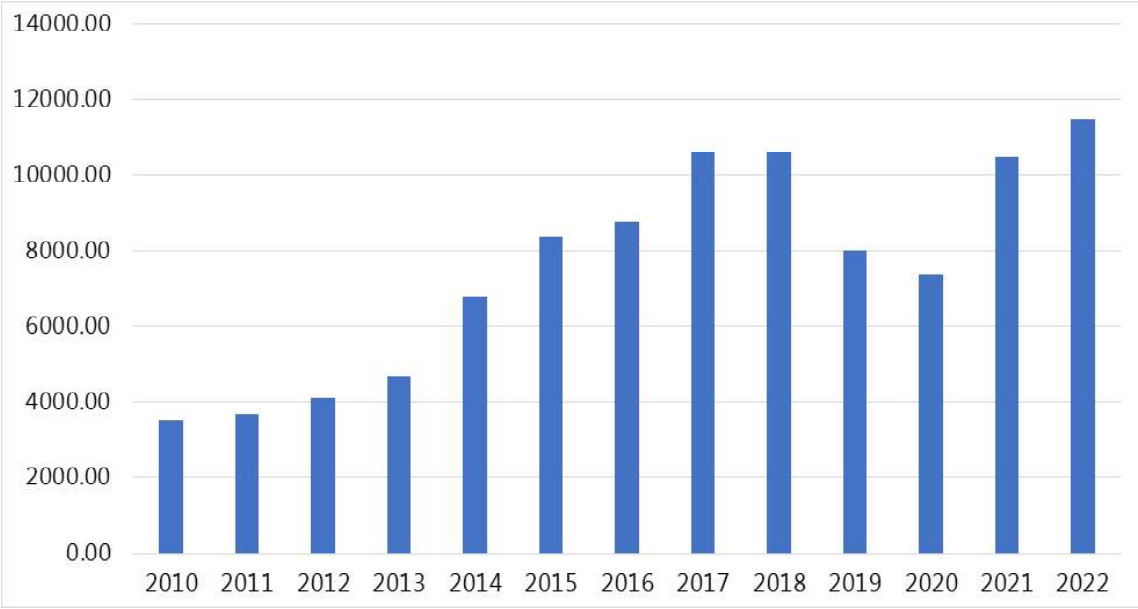
Table 2 : Descriptive Statistics and Test for Normal Probability Model

Descriptive Statistics													
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252.00	247.00	251.00	250.00	244.00	248.00	247.00	248.00	246.00	245.00	252.00	247.00	36.00
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	3537.36	3671.01	4112.66	4703.11	6771.19	8360.27	8776.34	10597.03	10597.34	8014.20	7346.09	10482.33	11498.54
Std. Deviation	423.11	166.43	310.52	317.28	1138.98	331.64	930.93	623.80	953.22	571.21	1175.20	567.07	181.11
Coefficient of Variation	0.12	0.05	0.08	0.07	0.17	0.04	0.11	0.06	0.09	0.07	0.16	0.05	0.02
Skewness	0.29	0.40	0.06	0.39	-0.03	-0.20	0.00	-0.10	-0.81	-0.53	-0.55	0.51	-0.54
Kurtosis	-1.31	0.02	-0.19	-0.69	-1.41	-0.37	-1.10	-0.88	-0.72	-0.50	-0.55	0.02	-0.03
Shapiro-Wilk	0.91	0.99	0.99	0.96	0.92	0.99	0.96	0.96	0.85	0.95	0.94	0.98	0.95
P-value of Shapiro-Wilk	< .001	0.01	0.07	< .001	< .001	0.08	< .001	< .001	< .001	< .001	< .001	< .001	0.12
Minimum	2864.00	3304.80	3356.10	4092.90	4912.40	7464.30	6949.40	9300.30	8578.05	6763.75	4517.75	9272.50	11107.15
Maximum	4259.90	4213.40	4847.30	5351.70	8594.90	9099.60	10458.00	12009.00	11974.50	9182.45	9311.10	12061.80	11881.25

Source: From researcher's data analysis

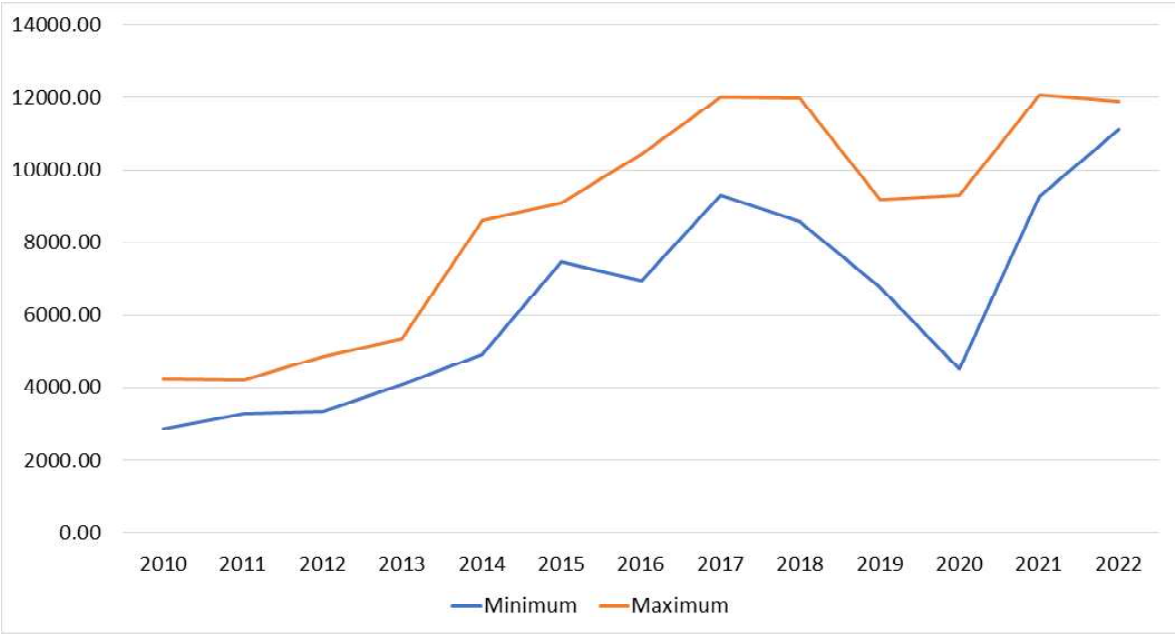
The above table gives the descriptive statistics for the AUTO indices for the period 2010-2022. The following graph gives the fluctuation of the mean index values over the years. One can observe that the average index values are in an increasing trend till the year 2018, dip in the values for the years 2019 and 2020 and again an increment for the years 2021 and 2022. One can look for specific events that have led to the decrement in the two years (COVID-19 could be a possible event). Similarly, one can study the events that have led to the increment. From the test for normality, one can observe that the movement of the index values is non-normal for all the years except for the years 2013, 2015 and 2012. Hence, we measure the tail index and classify the index movement. From the coefficient of variation, one can note that the change in the index values is consistent in the year 2022. That is, the deviation of values from the mean is low during the year 2022, followed by 2015, 2011, 2017, 2019, 2013, 2012, 2021, respectively.

Graph-2 gives the movement of minimum and maximum index values over the years and one can note that except for the years 2019, 2020, there is an increasing trend in the values. We study the behaviour of the minimum and maximum using extremal index values.



Graph 1 : Mean value for the AUTO indices

Source: From researcher's data analysis



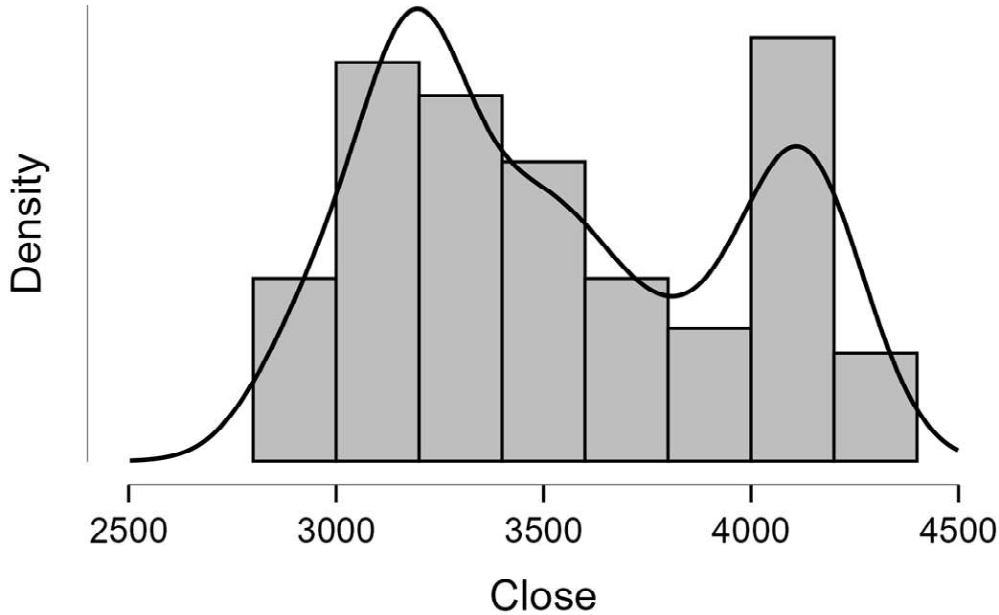
Graph 2 : Movement of minimum and maximum AUTO index values

Source: From researcher's data analysis

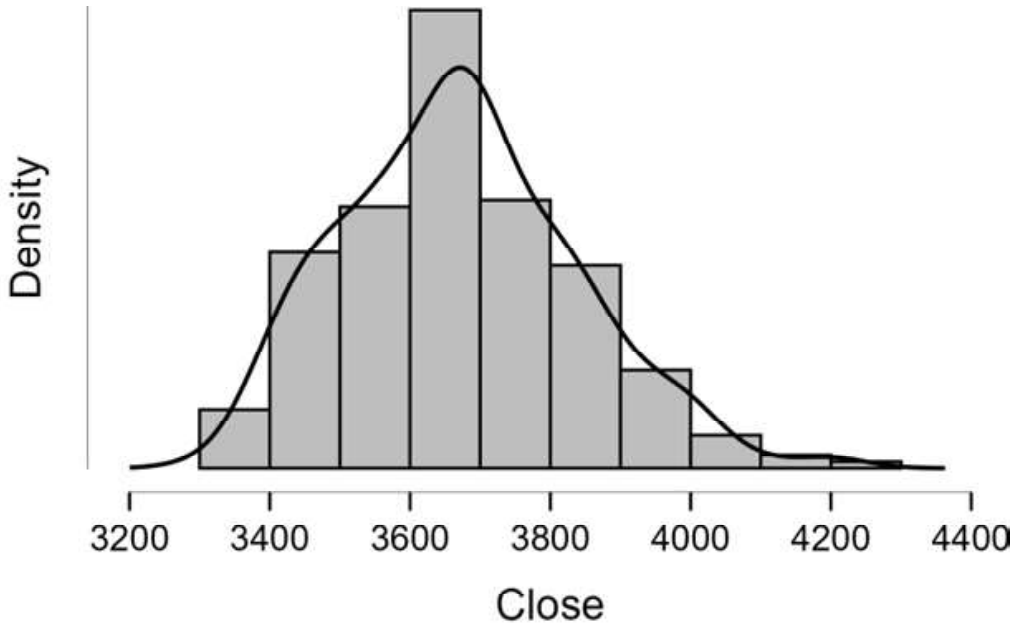
The following distribution plots give the behaviour of the index values over the years and also the tail behaviour of the index variables over the years. This motivates one to observe the tail behaviour of the index over the years.

Distribution Plots

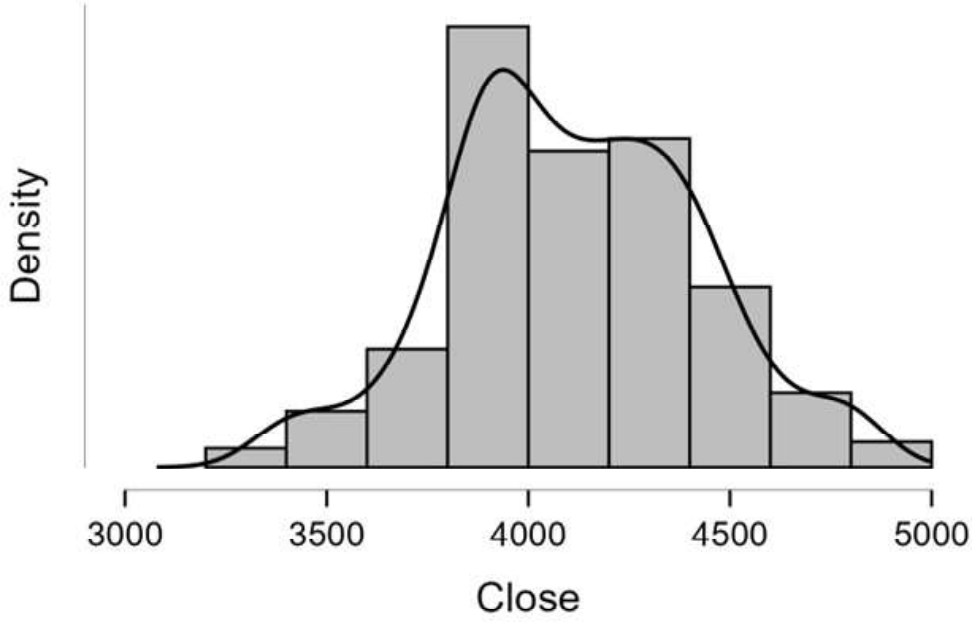
2010



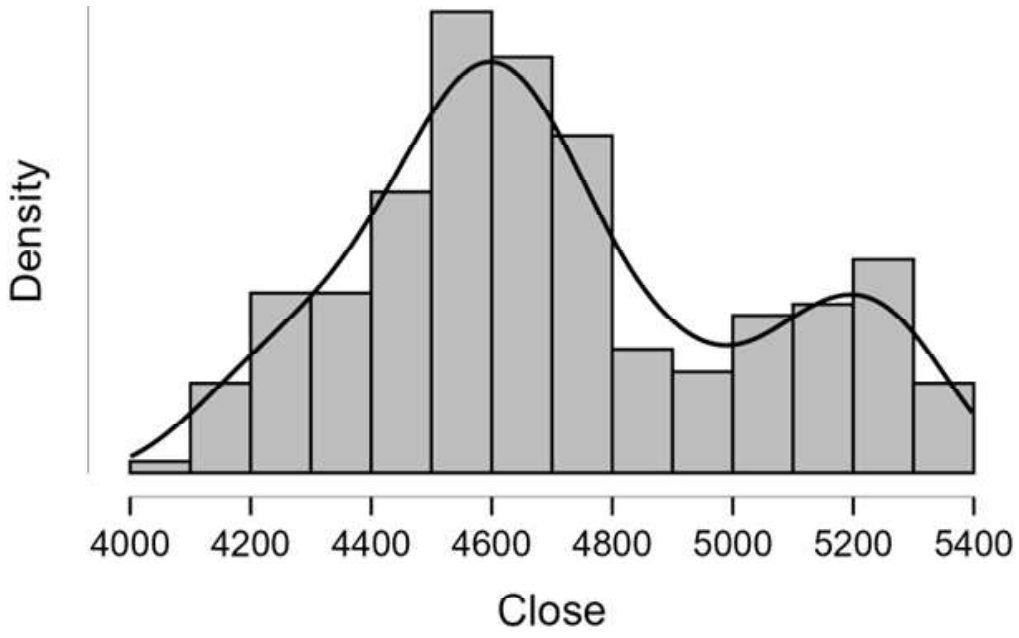
2011


Density
3200
3400
3600
3800
4000
4200
4400
Close

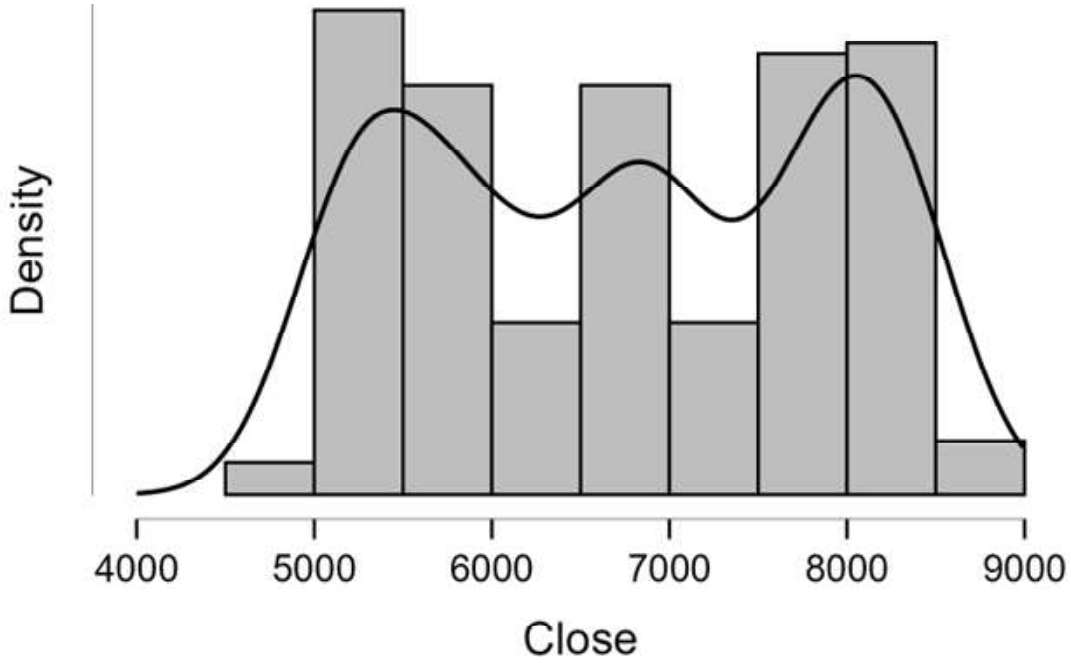
2012


Density
3000
3500
4000
4500
5000
Close

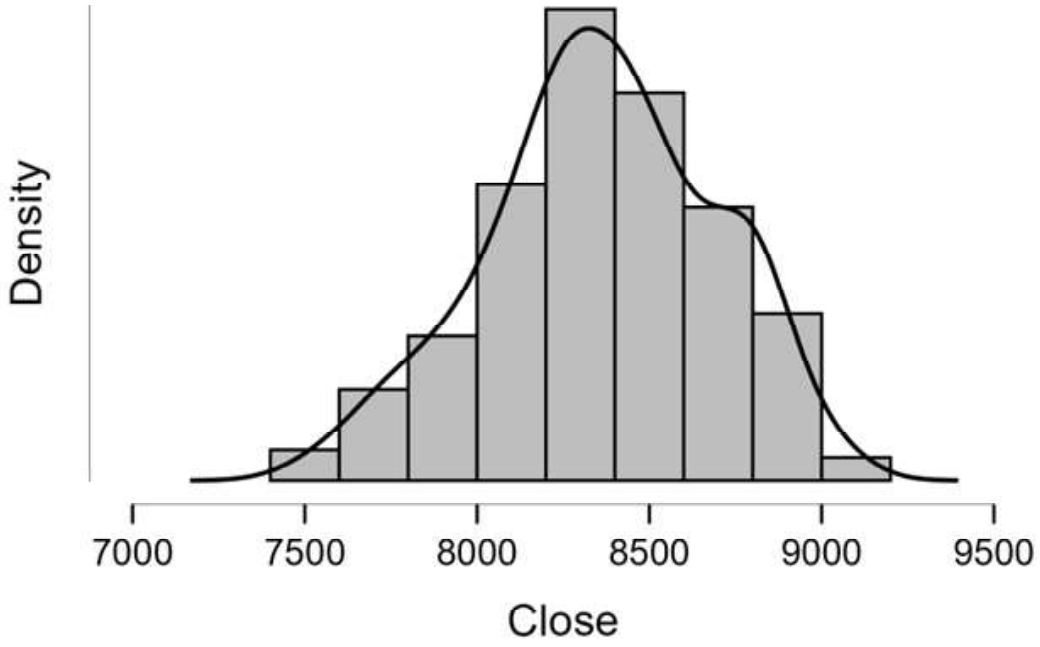
2013


Density
4000
4200
4400
4600
4800
5000
5200
5400
Close

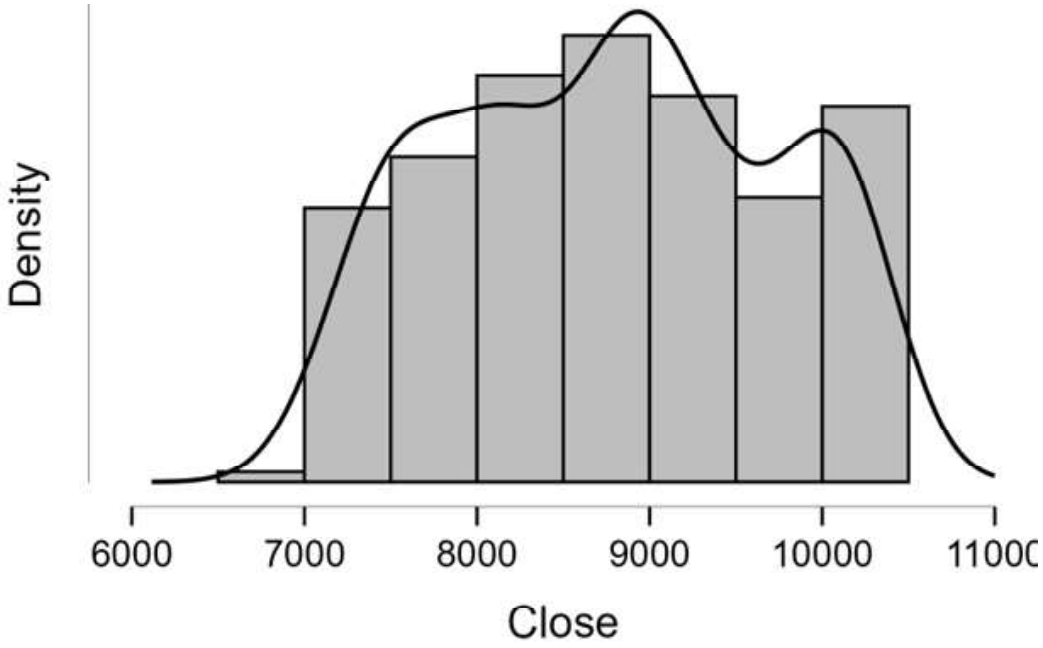
2014


Density
4000
5000
6000
7000
8000
9000
Close

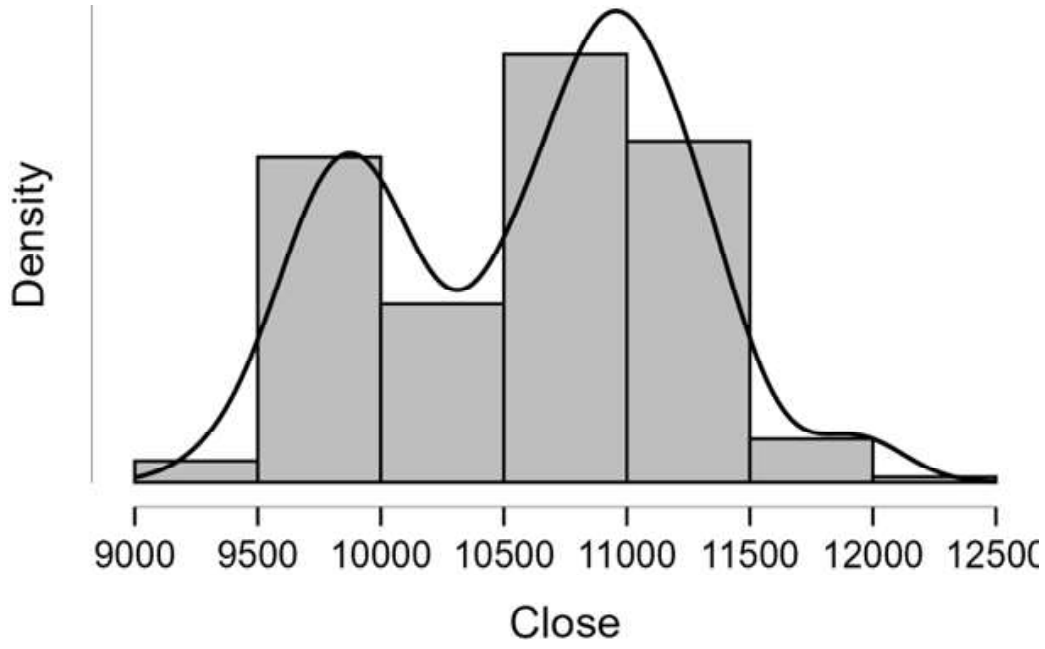
2015


Density
7000
7500
8000
8500
9000
9500
Close

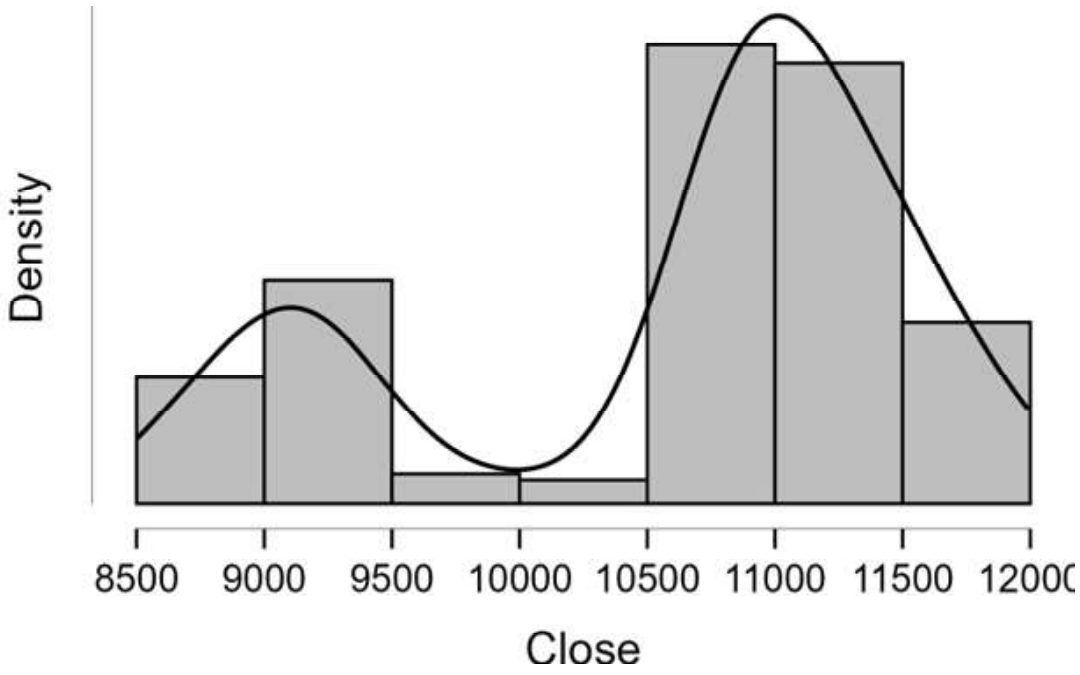
2016


Density
6000
7000
8000
9000
10000
11000
Close

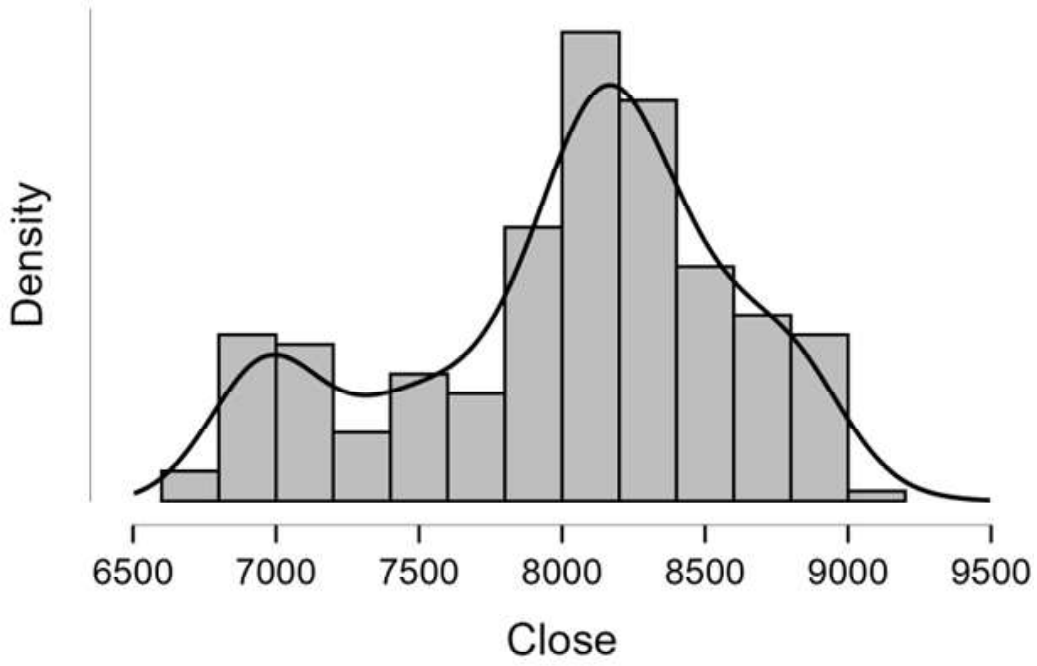
2017


Density
9000
9500
10000
10500
11000
11500
12000
12500
Close

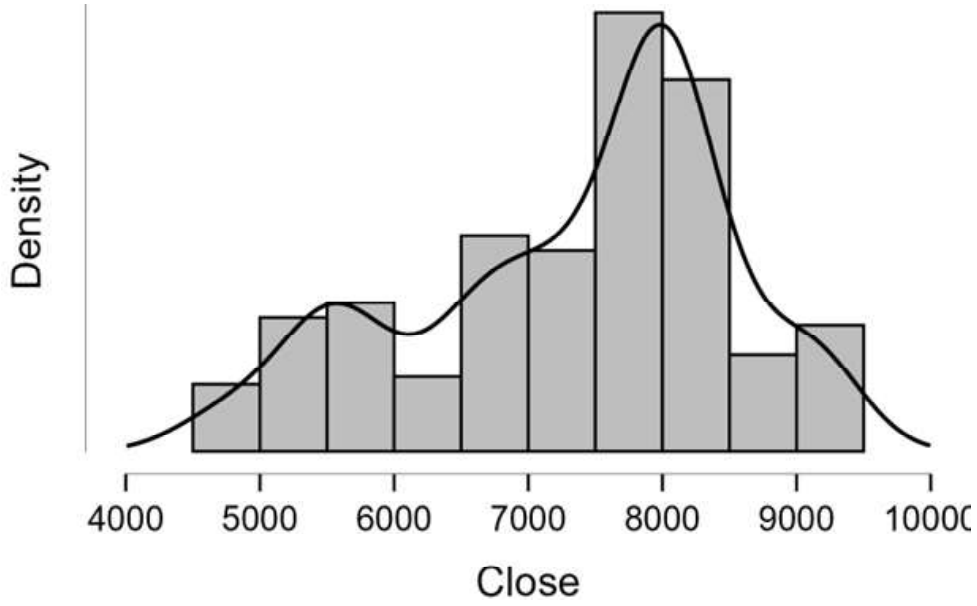
2018


Density
8500
9000
9500
10000
10500
11000
11500
12000
Close

2019


Density
6500
7000
7500
8000
8500
9000
9500
Close

2020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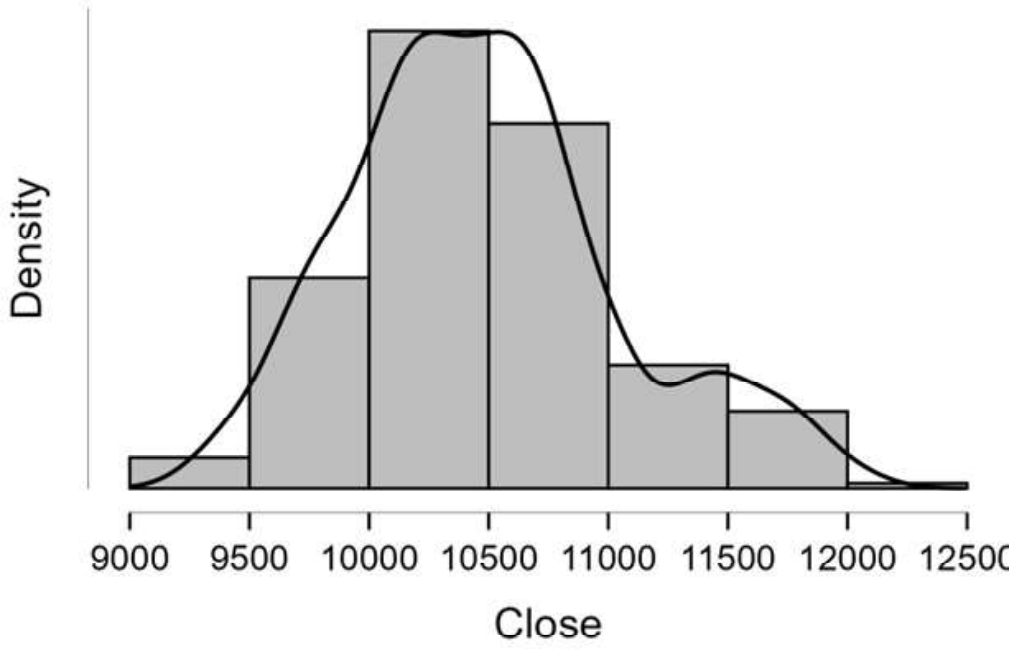
2021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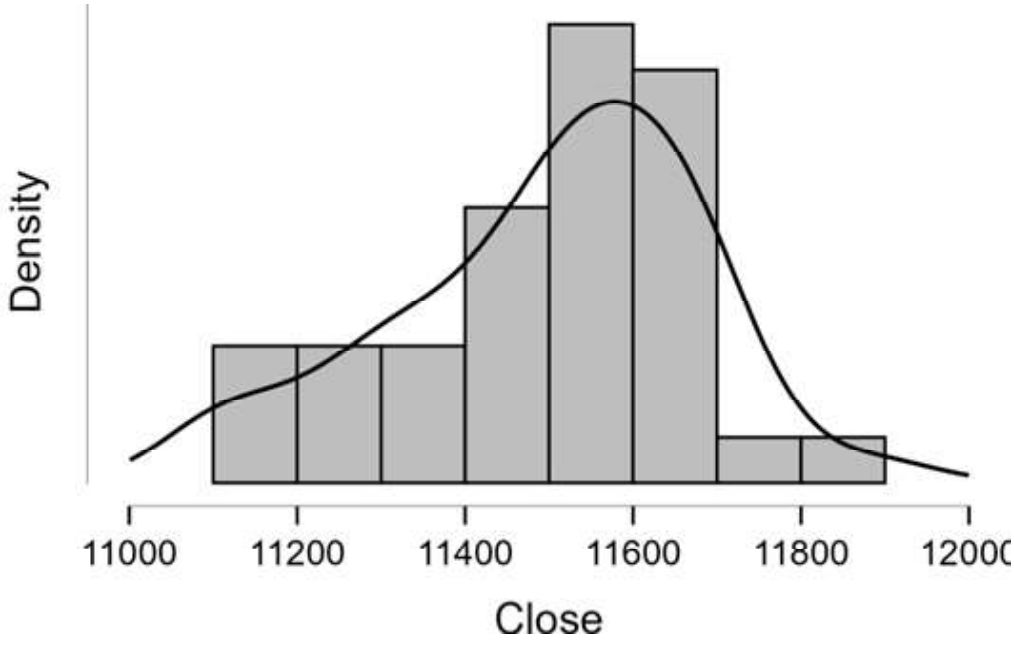
2022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Model for minimum and maximum index variable

Table 3 : Models for Maximum and Minimum Index Variables-Auto Indices

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.1156	8.6529	Weibull	-0.6035	1.6570	Weibull
2011	-0.1548	6.4584	Weibull	-0.4006	2.4962	Weibull
2012	-0.2585	3.8680	Weibull	-0.2902	3.4459	Weibull
2013	-0.1498	6.6770	Weibull	-0.4517	2.2138	Weibull
2014	-0.5876	1.7019	Weibull	-0.5544	1.8036	Weibull
2015	-0.3673	2.7228	Weibull	-0.2230	4.4848	Weibull
2016	-0.4183	2.3905	Weibull	-0.3940	2.5381	Weibull
2017	-0.3222	3.1038	Weibull	-0.2853	3.5056	Weibull
2018	-0.6694	1.4939	Weibull	0.1771	5.6458	Fréchet
2019	-0.4435	2.2546	Weibull	-0.0911	10.9747	Weibull
2020	-0.5110	1.9568	Weibull	-0.0631	15.8597	Weibull
2021	-0.1281	7.8046	Weibull	-0.4141	2.4150	Weibull
2022	-0.3793	2.6364	Weibull	-0.1377	7.2597	Weibull

Source: From Researcher's Data Analysis

From the above table, one can note that the Weibull distribution is the most repeated distribution that best suits the behaviour of both minimum and maximum index variables. Using this one can compute the probabilities related to the maximum or minimum crossing a given threshold. Only for the year 2018, the minimum index variable has to be modelled by the Fréchet distribution.

Tail index and classification of the Index

Table 4 : Tail Index for the Auto Indices

	Shape	Scale	Comments based on the tail index
2010	4.827261	2864	heavy-tailed and moments of higher-order exists
2011	9.463753	3304.8	heavy-tailed and moments of higher-order exists
2012	4.915472	3356.1	heavy-tailed and moments of higher-order exists
2013	7.204686	4092.9	heavy-tailed and moments of higher-order exists
2014	3.212455	4912.4	heavy-tailed and moments of higher-order exists
2015	8.751193	7464.3	heavy-tailed and moments of higher-order exists
2016	4.320131	6949.4	heavy-tailed and moments of higher-order exists
2017	7.643229	9300.3	heavy-tailed and moments of higher-order exists
2018	4.75505	8578.05	heavy-tailed and moments of higher-order exists
2019	5.89711	6763.75	heavy-tailed and moments of higher-order exists
2020	2.086851	4517.75	heavy-tailed and only mean exists
2021	8.127571	9272.5	heavy-tailed and moments of higher-order exists
2022	26.79372	11107.15	heavy-tailed and moments of higher-order exists

Source: From researcher's data analysis

One can observe from the above table that the tail behaviour for the AUTO index over the years is heavy-tailed and moments of higher-order exists. For the year 2020, only mean exists. This motivates one to study the stable index, which gives more information about the behaviour of the cumulative index variable. This helps one to understand the extent of impact the information generated on the stocks listed has on the index.

The index value for Stable Models

Table 5 : Stable Index and Model-Auto Indices

	α	β	σ	μ	Model
2010	2	0	326.02	3540.55	Normal
2011	1.997914	0	117.271	3672.6	Stable
2012	2	0	221.224	4113.22	Normal
2013	2	0	230.862	4706.64	Normal
2014	2	0	889.827	6770.44	Normal
2015	2	0	239.518	8358.65	Normal
2016	2	0	712.381	8776.46	Normal
2017	2	0	470.152	10595	Normal
2018	1.749886	-1	603.428	10808.8	Stable
2019	1.987775	0	402.58	8004.56	Stable
2020	2	0	835.346	7327.16	Normal
2021	1.937066	1	386.162	10454.3	Stable
2022	1.943415	-1	122.567	11506.2	Stable

Source: From researcher's data analysis

From the above table one can note that, for many years Normal model is appropriate for the cumulative AUTO index variable. This indicates that the information generated on the index didn't have much impact on the behaviour of the cumulative index. In other words, the extreme index values that are resultant of the information generated are neutralized by the other information generated and finally the behaviour has shifted from stable to normal. In few years the model that suits the cumulative index behaviour is stable and, in these years, the extreme index values have dominated the cumulative index behaviour. Overall, the AUTO index could sustain the shocks generated by extreme information and we conclude that AUTO index is not much affected by the extreme values. It is interesting to note that the tails of the index variable are heavy but when aggregated the cumulative index behaviour tends towards normal behaviour, which is a good sign for the investors. Because individually the behaviour of the index variable is affected by the information generated and the same is neutralized due to the cumulative effect.

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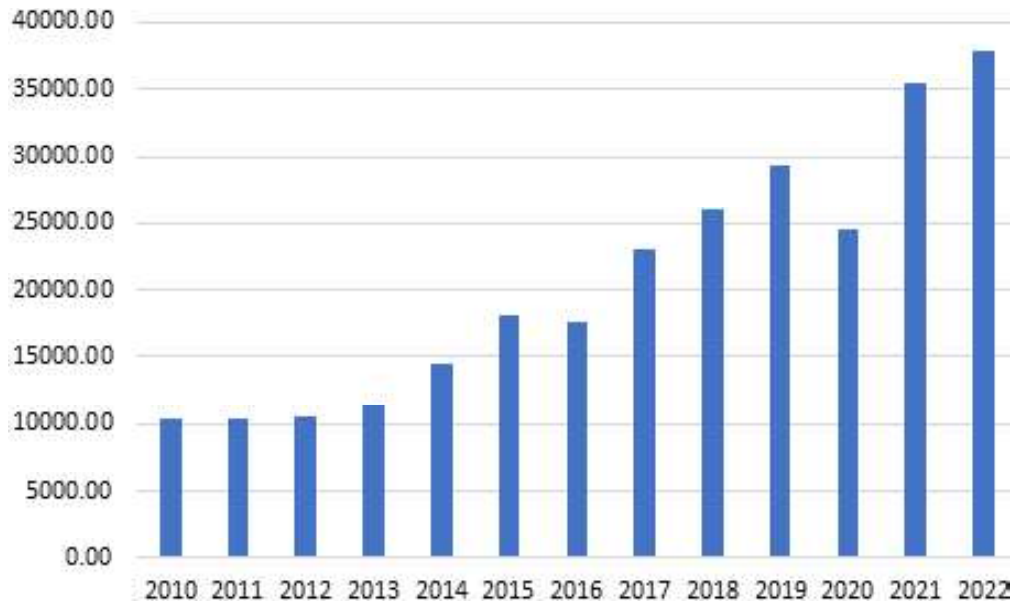
Table 6 : Descriptive Statistics and Test for Normal Probability Model

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252.00	247.00	251.00	250.00	244.00	248.00	247.00	248.00	246.00	245.00	252.00	247.00	37.00
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	10358.87	10297.56	10508.87	11414.56	14522.21	18095.25	17560.31	23066.71	26106.83	29360.10	24558.08	35387.48	37977.03
Std. Deviation	1387.09	985.52	927.76	1047.62	2483.19	938.59	1743.57	2067.23	1058.28	1676.58	4530.61	2214.53	641.72
Coefficient of Variation	0.13	0.10	0.09	0.09	0.17	0.05	0.10	0.09	0.04	0.06	0.18	0.06	0.02
Skewness	0.44	-0.56	0.19	-0.45	-0.21	0.03	-0.40	-0.69	0.10	0.00	0.35	0.07	-0.20
Kurtosis	-1.16	-0.56	-0.05	-0.43	-0.95	-0.54	-0.97	-0.54	-0.74	-1.27	-1.34	-0.09	0.07
Shapiro-Wilk	0.92	0.95	0.97	0.97	0.94	0.98	0.95	0.92	0.98	0.95	0.90	0.99	0.99
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	0.001	< .001	< .001	0.01	< .001	< .001	0.01	0.95
Minimum	8223.20	7798.50	7995.00	8664.20	10102.00	15790.00	13555.00	17891.00	23670.40	26573.40	16917.65	30284.55	36421.90
Maximum	13268.00	11894.00	12510.00	13317.00	18782.00	20555.00	20426.00	25891.00	28320.00	32412.35	32443.85	41238.30	39330.50

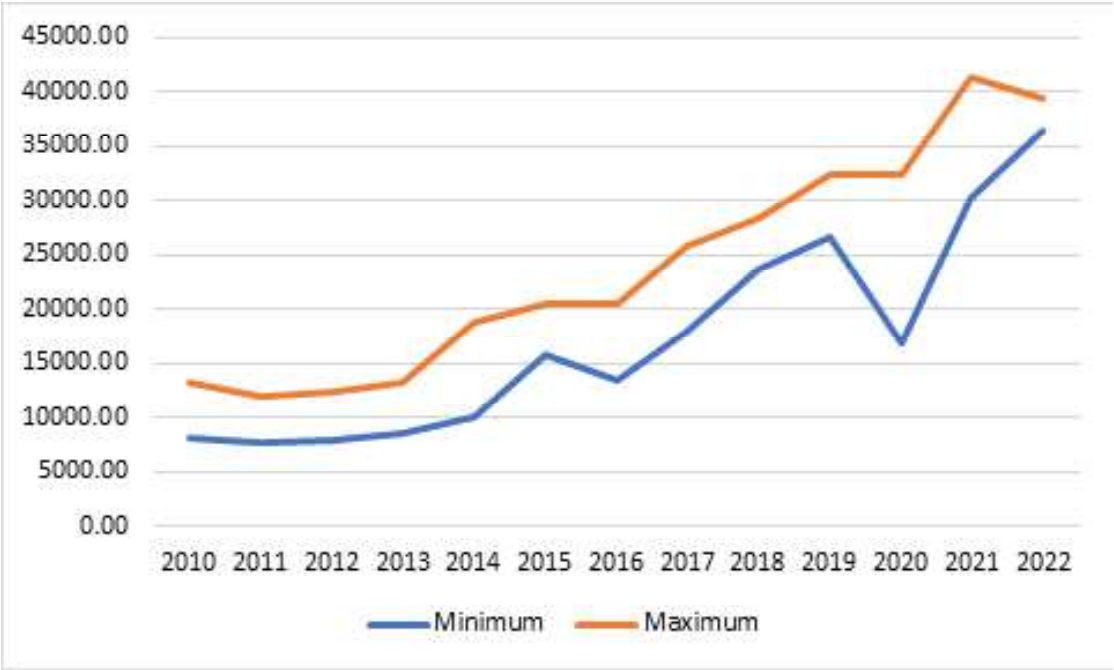
Source: From Researcher's Data Analysis

One can note from the table and the graph- that, the mean index values over the years are in an increasing trend except for the year 2020. Also, except for the year 2022 for all the years normality is not satisfied by the data. The maximum and minimum index values have a dip during the year 2020 and for all other years the trend is increasing. From the distribution plots presented below one can observe that the tails are heavy, and the index values presented in the table below gives the thickness of the tails.



Graph 3 : Mean values for the Bank Index

Source: From Researcher's Data Analysis

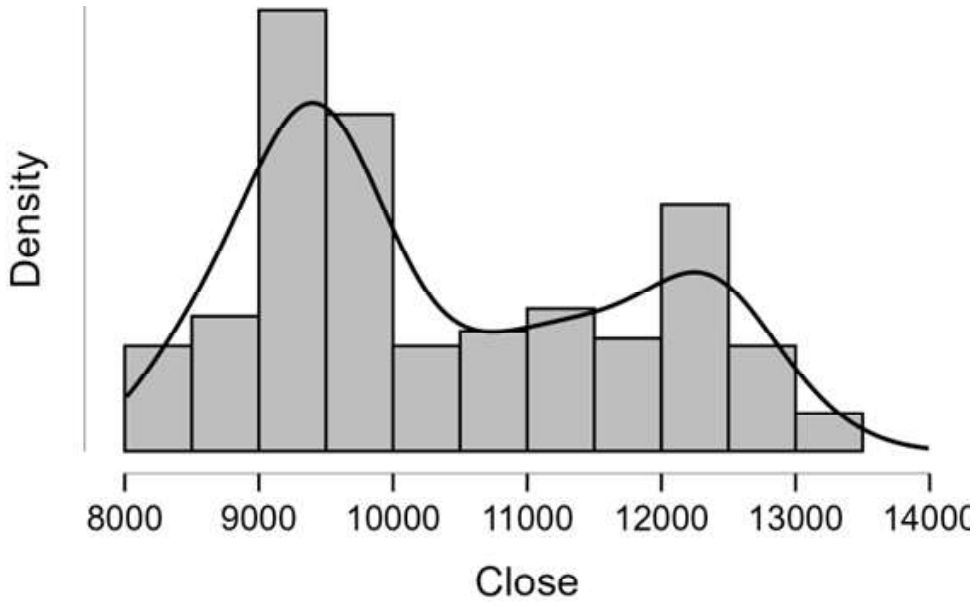


Graph 4 : Maximum and Minimum values of the Index

Source: From Researcher's Data Analysis

Distribution Plots

2010



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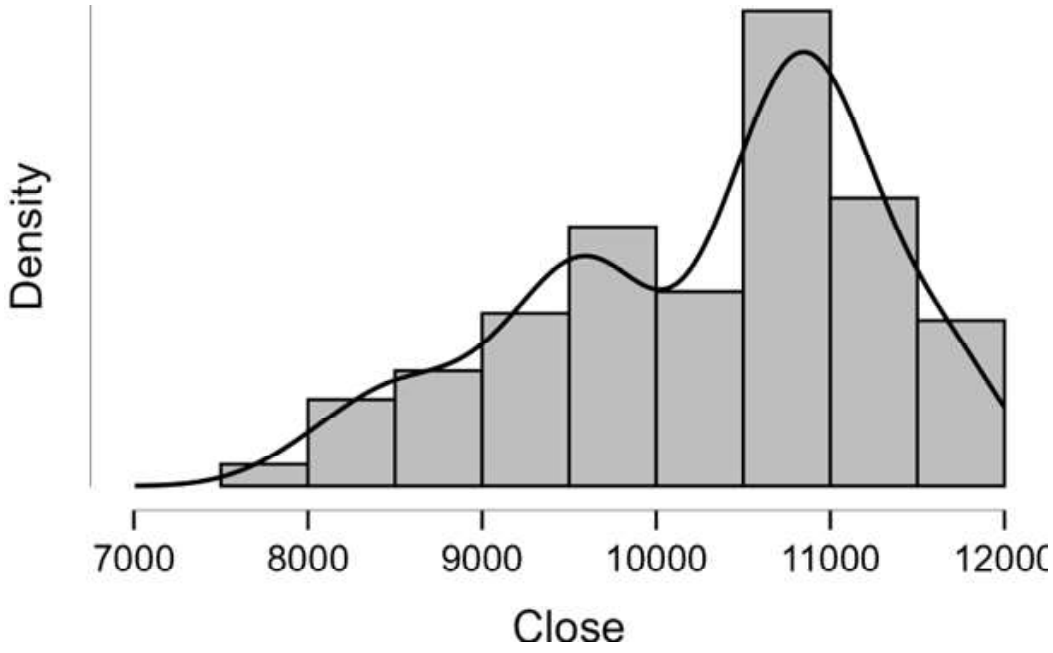

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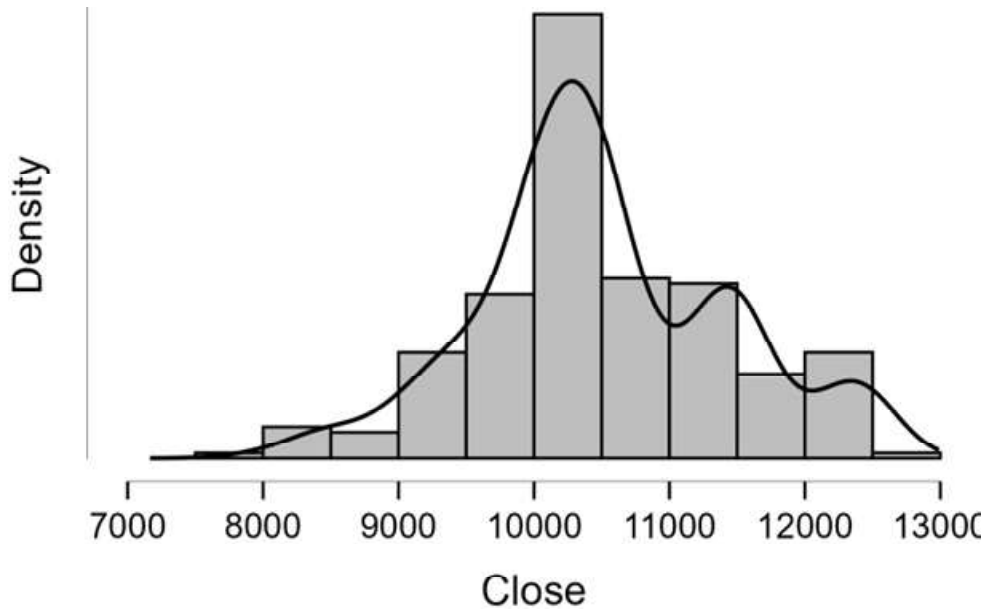
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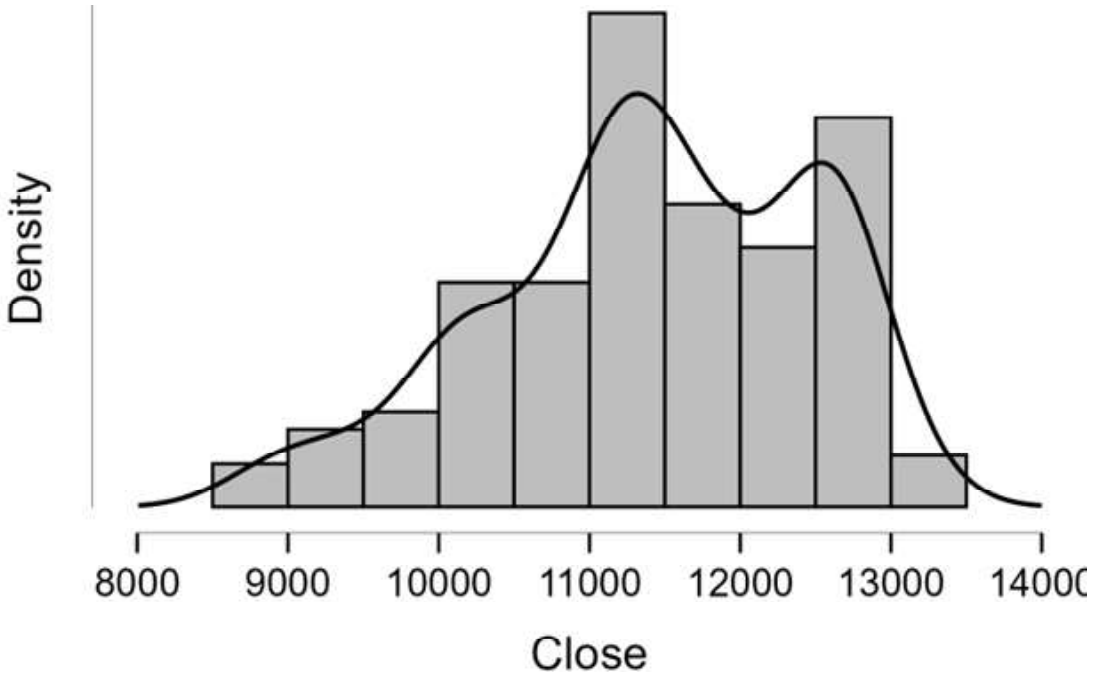
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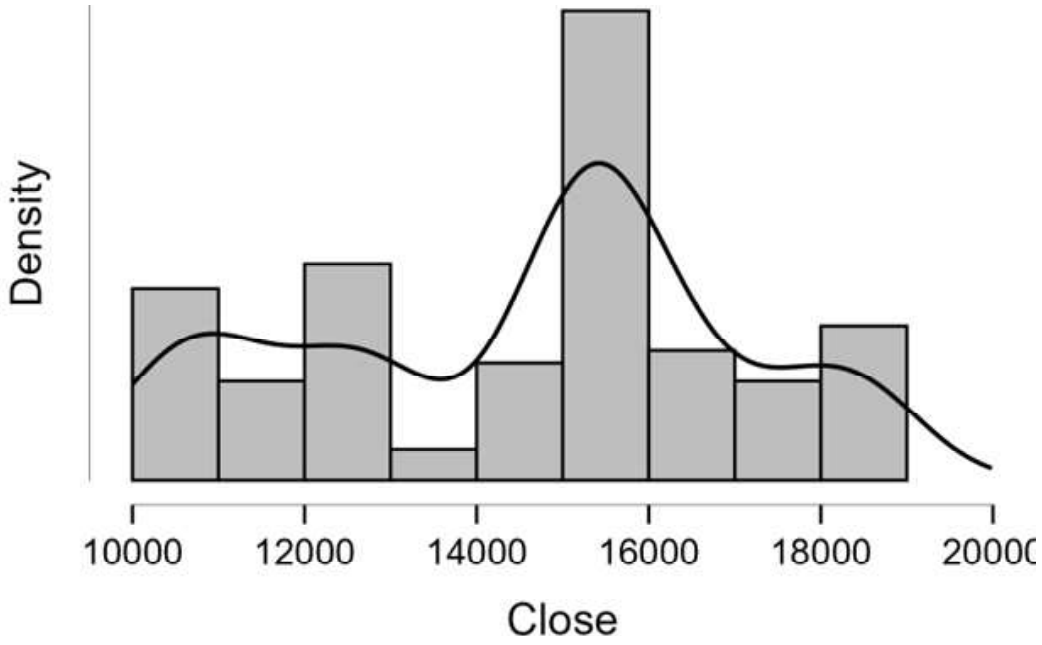
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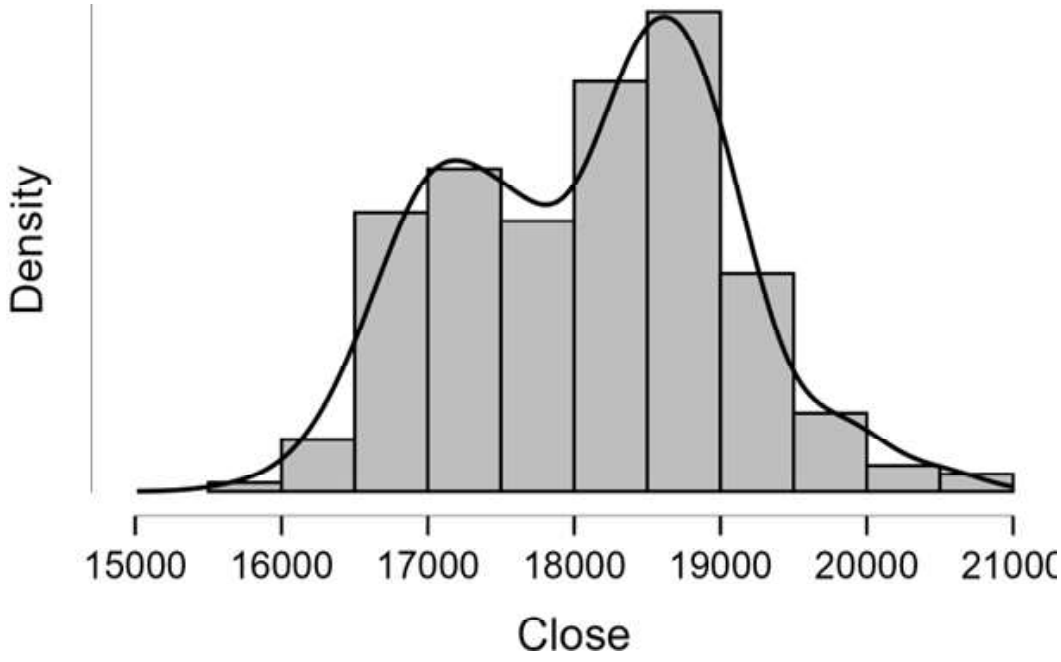
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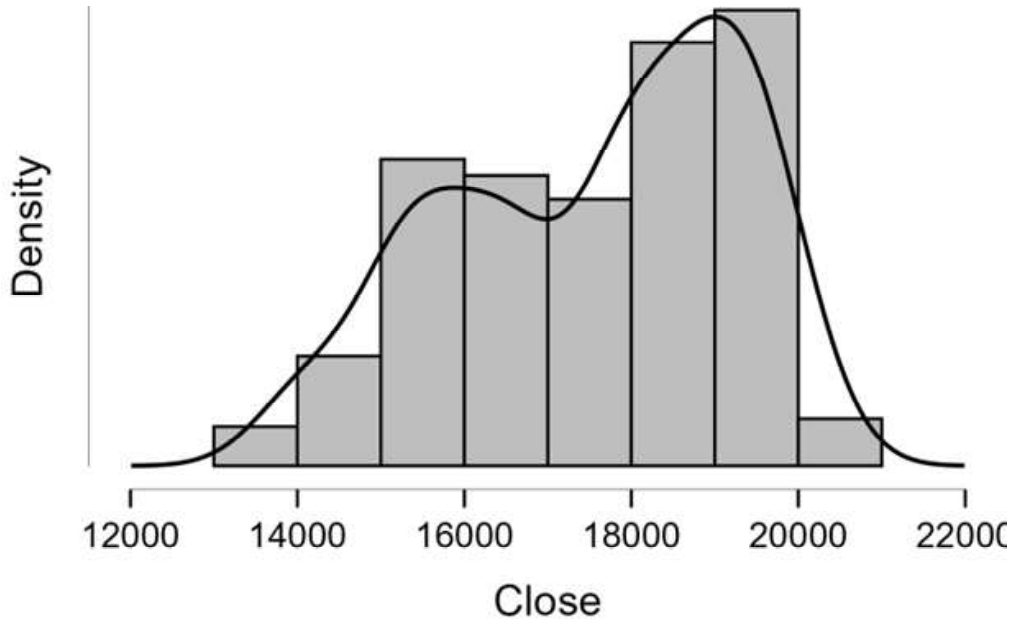
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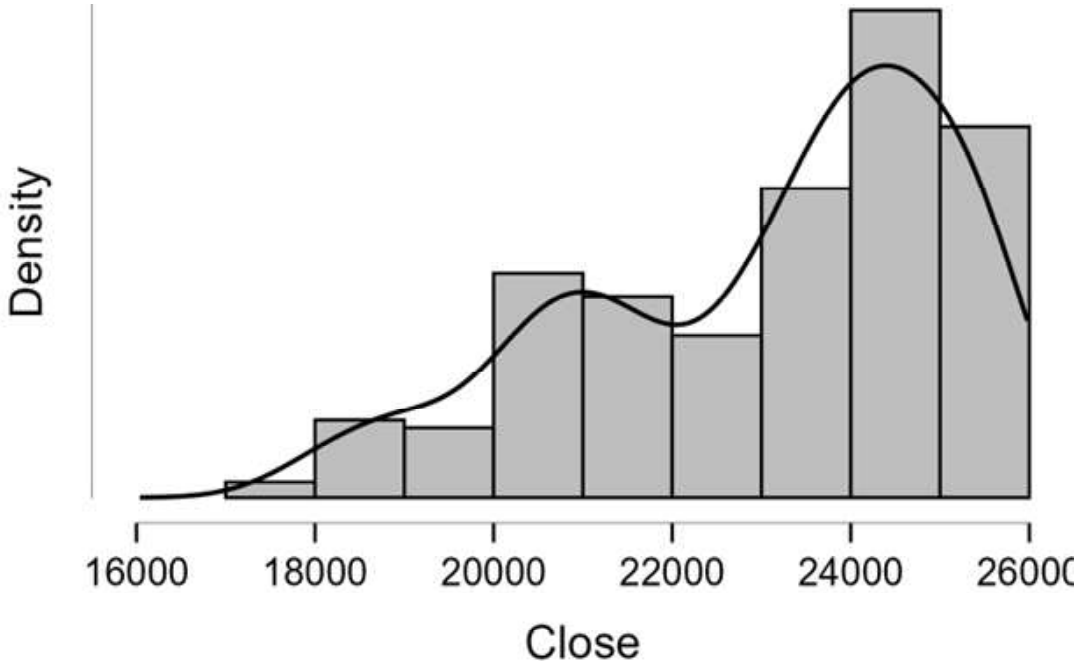
2017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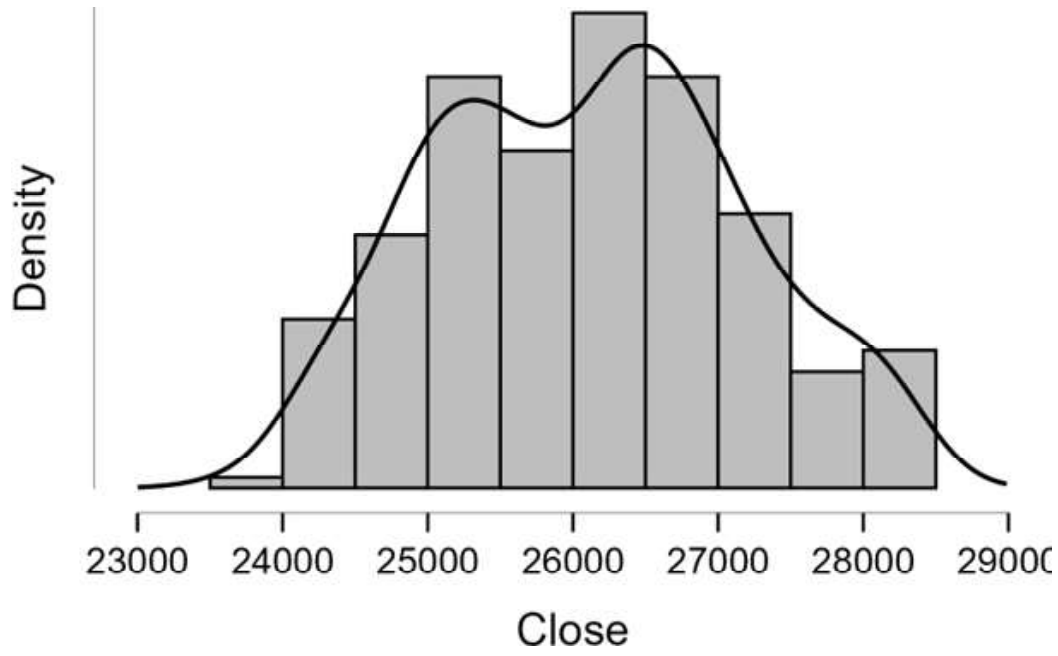
2018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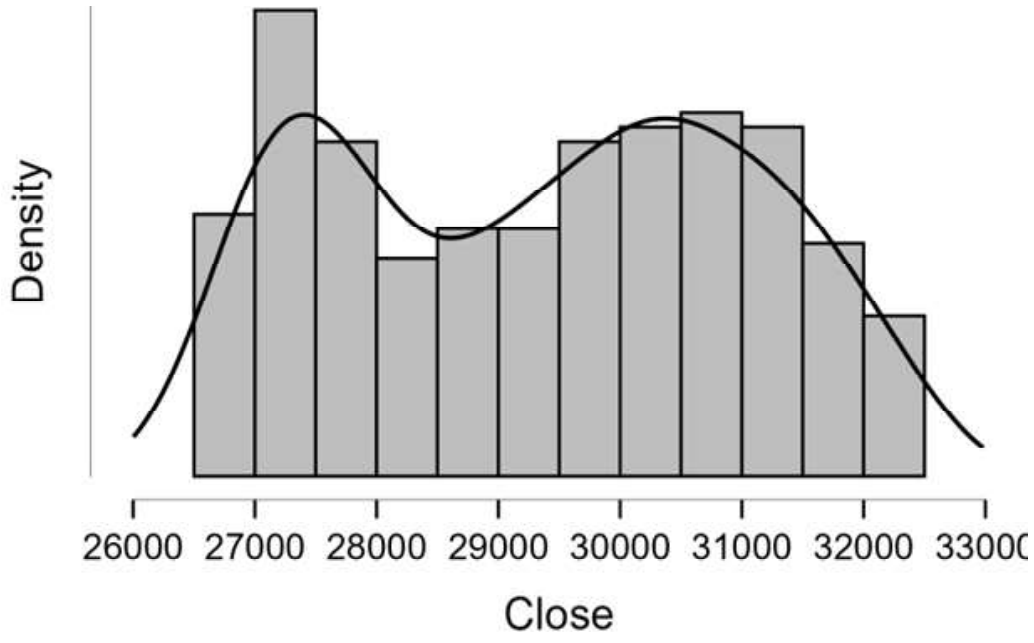
2019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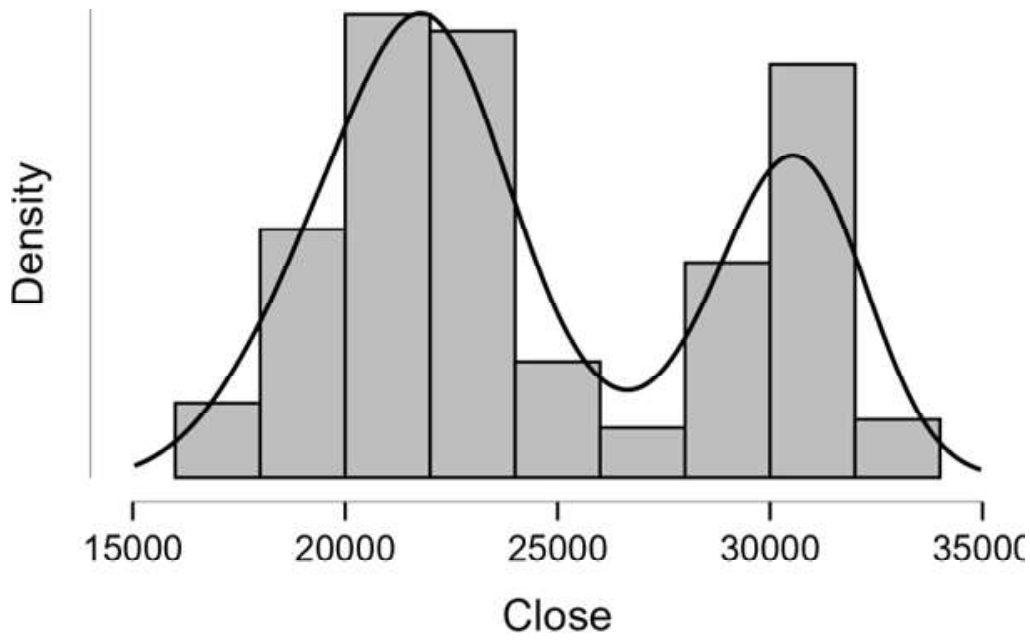
2020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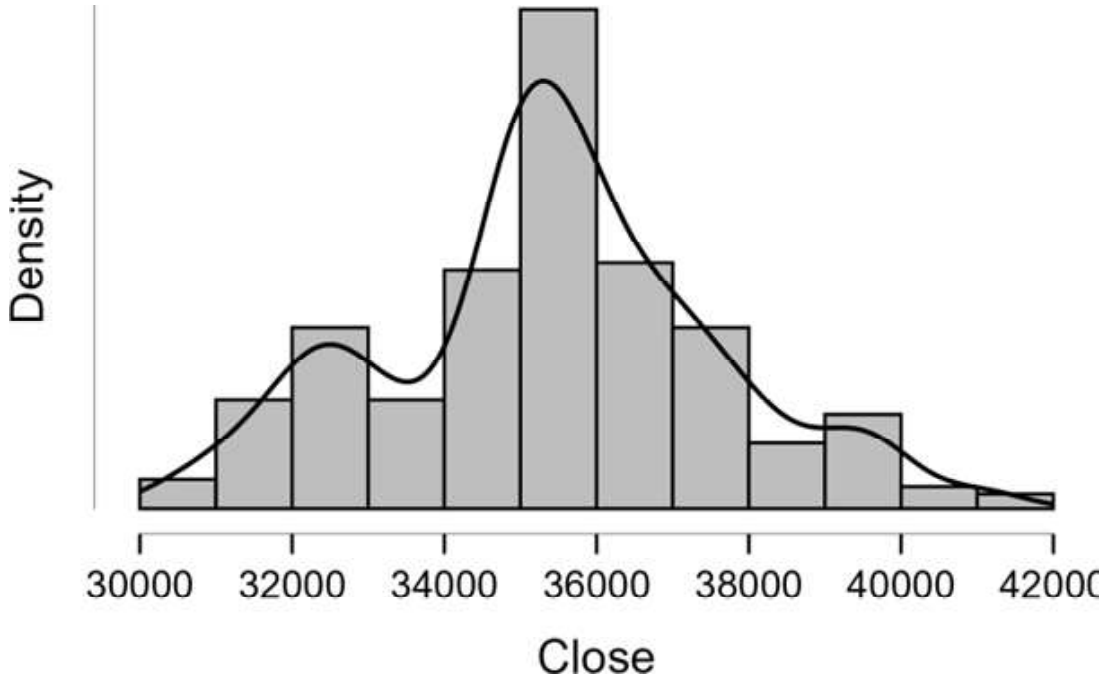
2021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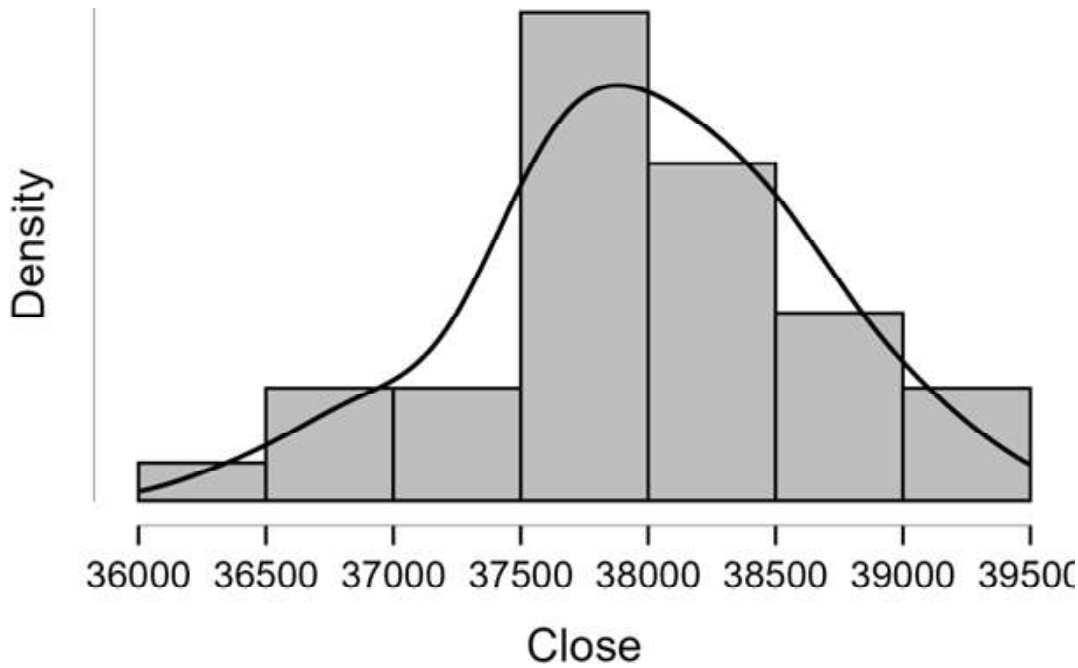

Source: From researcher's data analysis

Table 7 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	0.0382	26.1621	Fréchet	-0.6390	1.5649	Weibull
2011	-0.5613	1.7815	Weibull	-0.0368	27.1613	Weibull
2012	-0.2576	3.8826	Weibull	-0.2971	3.3664	Weibull
2013	-0.4866	2.0549	Weibull	-0.1096	9.1266	Weibull
2014	-0.4564	2.1909	Weibull	-0.1933	5.1735	Weibull
2015	-0.2609	3.8325	Weibull	-0.3240	3.0865	Weibull
2016	-0.5691	1.7573	Weibull	-0.0515	19.4338	Weibull
2017	-0.7062	1.4160	Weibull	0.1540	6.4950	Fréchet
2018	-0.2578	3.8791	Weibull	-0.3509	2.8499	Weibull
2019	-0.4101	2.4386	Weibull	-0.5304	1.8855	Weibull
2020	-0.0338	29.5491	Weibull	-0.5248	1.9053	Weibull
2021	-0.2507	3.9894	Weibull	-0.2951	3.3883	Weibull
2022	-0.3424	2.9207	Weibull	-0.2261	4.4220	Weibull

Source: From researcher's data analysis

From the table one can note that, in all the cases the Weibull model suits the behaviour of the maximum and minimum random variables, except for the years 2010 and 2017.

Table 8 : Tail index and classification of the Index

	Shape	Scale	Comments based on the tail index
2010	4.435409	8223.2	heavy-tailed and moments of higher order exists
2011	3.60505	7798.5	heavy-tailed and moments of higher order exists
2012	3.651118	7995	heavy-tailed and moments of higher order exists
2013	3.629725	8664.2	heavy-tailed and moments of higher order exists
2014	2.833147	10102	heavy-tailed and only mean exists
2015	7.293408	15790	heavy-tailed and moments of higher order exists
2016	3.880505	13555	heavy-tailed and moments of higher order exists
2017	3.941778	17891	heavy-tailed and moments of higher order exists
2018	10.1393	23670.4	heavy-tailed and moments of higher order exists
2019	10.04124	26573.4	heavy-tailed and moments of higher order exists
2020	2.767928	16917.65	heavy-tailed and only mean exists
2021	6.406682	30284.55	heavy-tailed and moments of higher order exists
2022	22.2285	36421.9	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

One can observe that the tails of the index variable for all the years is heavy and during the years 2014 and 2020, the mean index value exists.

Table 9 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	1048.6	10374.9	Normal
2011	2	0	706.879	10282.3	Normal
2012	1.96833	1	642.895	10483.3	Stable
2013	2	0	755.435	11402.4	Normal
2014	2	0	1867.13	14507.8	Normal
2015	2	0	692.155	18095.2	Normal
2016	2	0	1308.81	17542.3	Normal
2017	1.98951	0	1458.5	23024.5	Stable
2018	2	0	788.337	26109.5	Normal
2019	2	0	1298.55	29359.8	Normal
2020	2	0	3481.37	24600.1	Normal
2021	1.98767	0	1553.04	35390.8	Stable
2022	1.99085	0	445.326	37973.8	Stable

Source: From researcher's data analysis

The values of the index for all the years are close to 2 and normality of the cumulative index variable for banking sector is preserved. Though the values for a few years is less than 2, they are not far away from and, this leads to a conclusion that they are almost normal. Hence we conclude that the information generated on the banking sector has a very low impact on the cumulative index variable.

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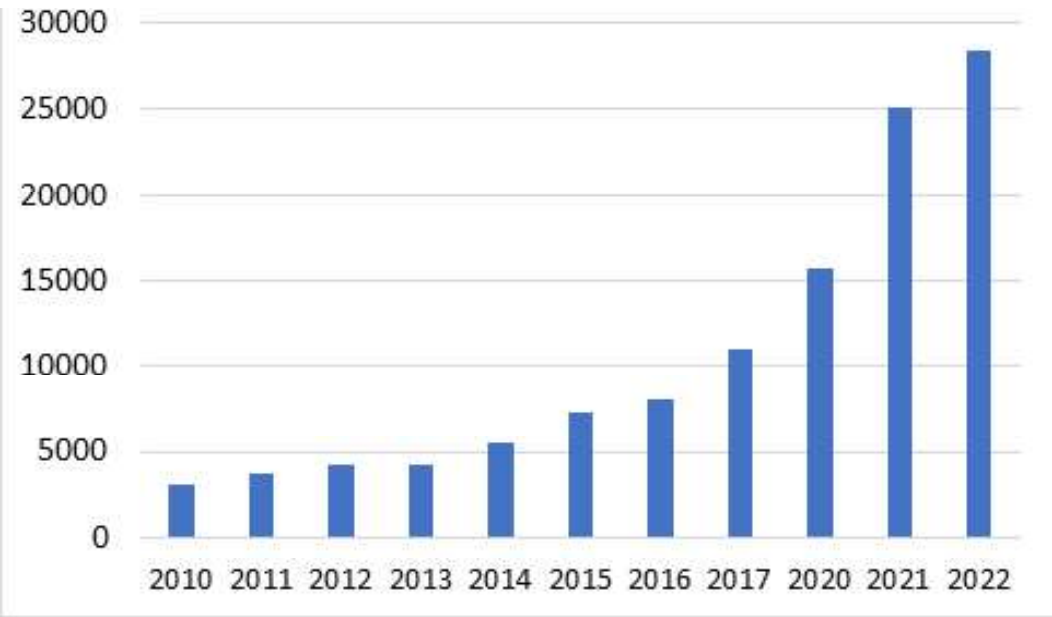
Table 10 : Descriptive Statistics and Test for Normal Probability Model

Descriptive Statistics											
	2010	2011	2012	2013	2014	2015	2016	2017	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	180	344	37
Missing	0	0	0	0	0	0	0	0	0	0	0
Mean	3131.921	3710.994	4211.39	4270.311	5561.912	7344.842	8105.25	10949.39	15735.39	25063.25	28419.58
Std. Deviation	499.128	255.229	372.248	376.015	1092.899	360.764	498.512	1626.6	1944.52	3244.706	1073.246
Skewness	0.275	-0.354	0.038	0.15	-0.265	0.397	0.222	0.319	-0.268	-0.046	0.25
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.181	0.131	0.388
Kurtosis	-1.341	-0.985	0.197	-1.186	-1.476	-0.873	-1.124	-0.355	-0.286	-1.529	-1.598
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.36	0.262	0.759
Shapiro-Wilk	0.917	0.952	0.957	0.954	0.89	0.955	0.95	0.969	0.963	0.903	0.858
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	2402.5	3145	3275.7	3543.1	3795.3	6661.9	7238	7729.6	11376.41	19920.61	26786.1
Maximum	4174.3	4162.9	5057.5	5011.3	7139.4	8160.5	9103.6	14593	19944.95	30469.05	30014.55

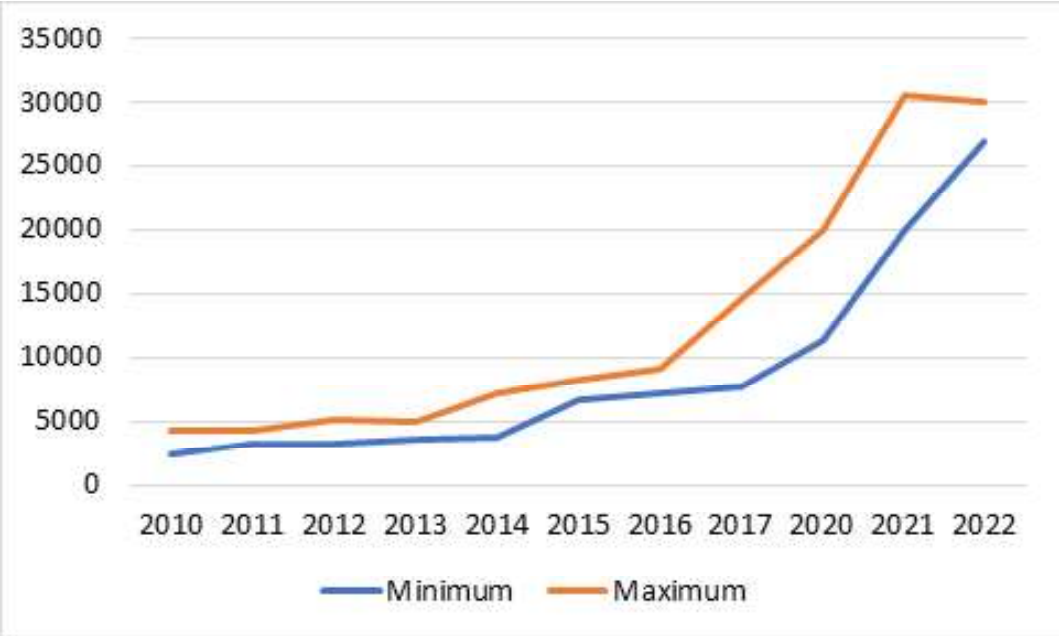
Source: From researcher's data analysis

The table and graph indicate that the mean index value is in an increasing trend and the maximum, minimum values also are in an increasing trend. This indicates that this index did not face much turbulence even during the crisis times. This can be judged by linking the movements with the individual stocks and the events around the sector. Also, the government policies and decisions on the same would have given sufficient support for the sector to sustain the crisis or the impct due to the information generated around the sector. From the Shapiro-Wilk test, one can observe that the normality assumption is not satisfied by the data. The same can be observed from the distribution plots and studying the tail index value will give a better understanding of the index movements over the years.



Graph 5 : Mean value of the index

Source: From researcher's data analysis

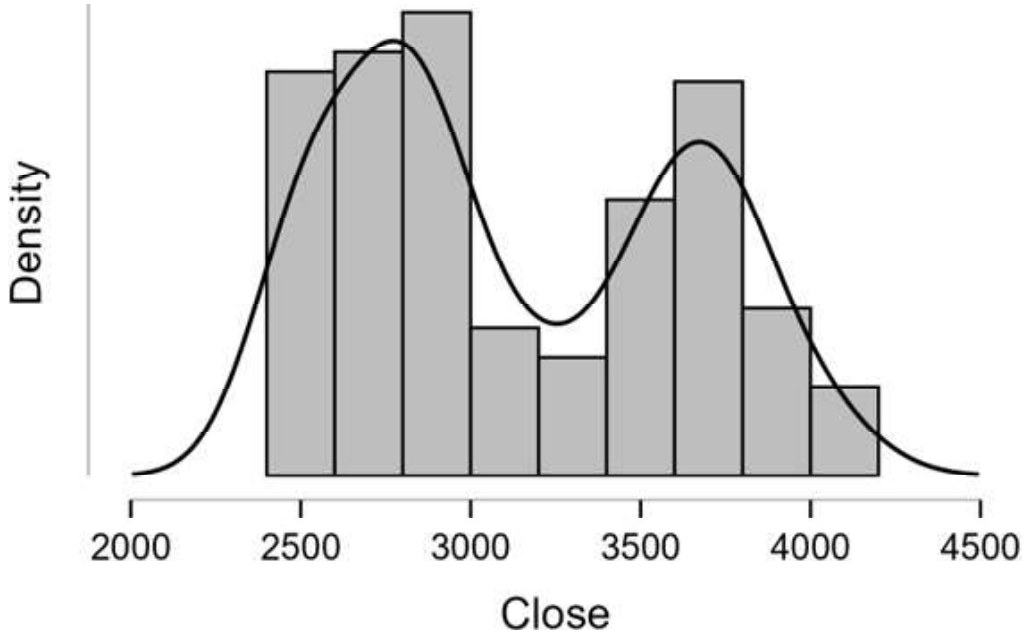


Graph 6 : Maximum and Minimum values

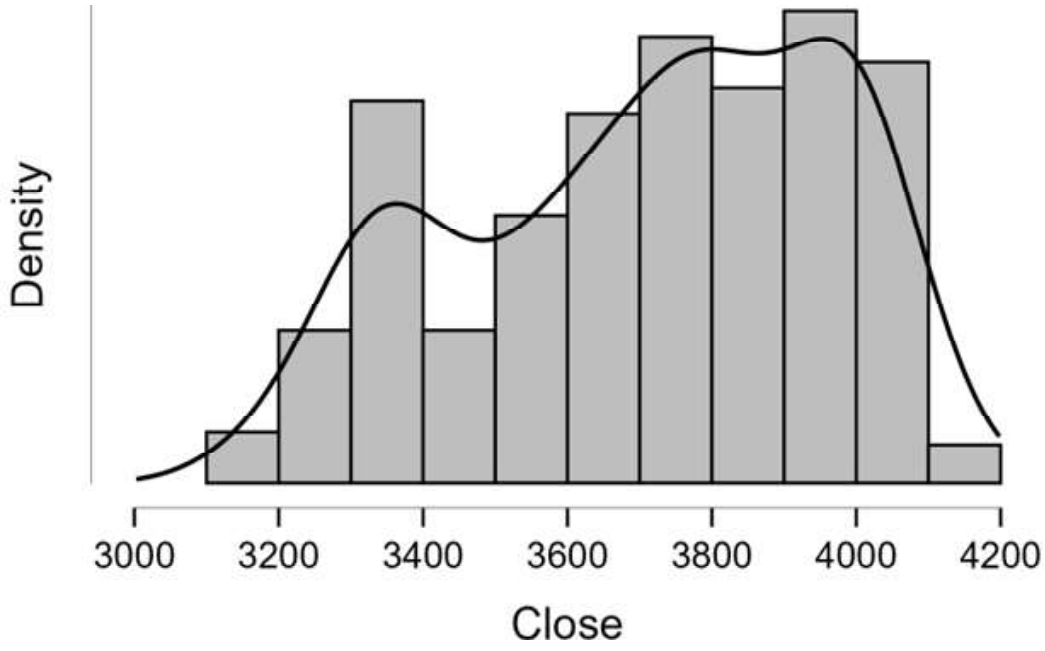
Source: From researcher's data analysis

Distribution Plots

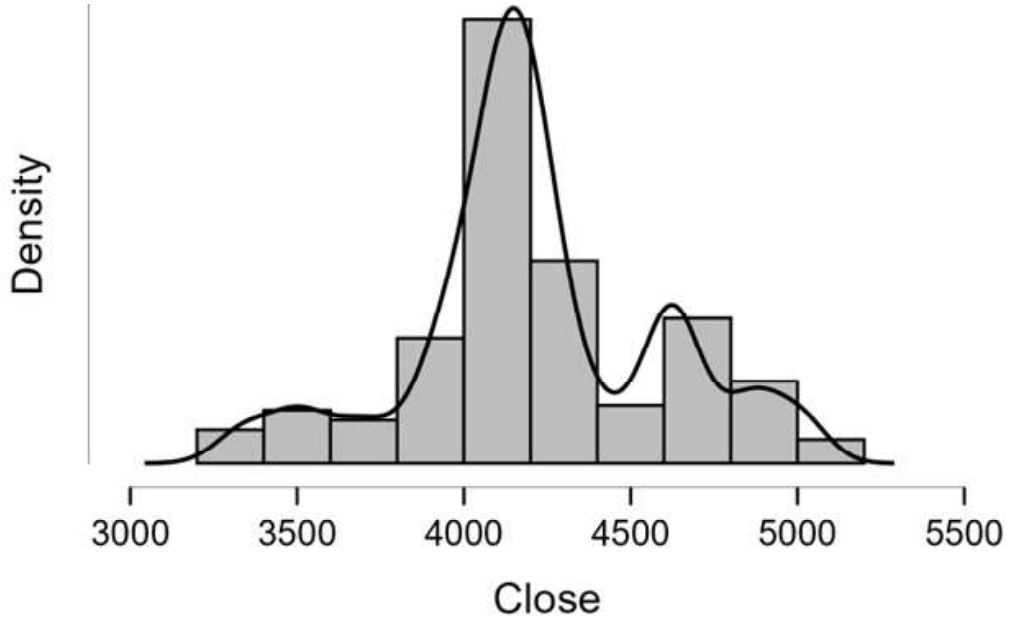
2010



2011



2012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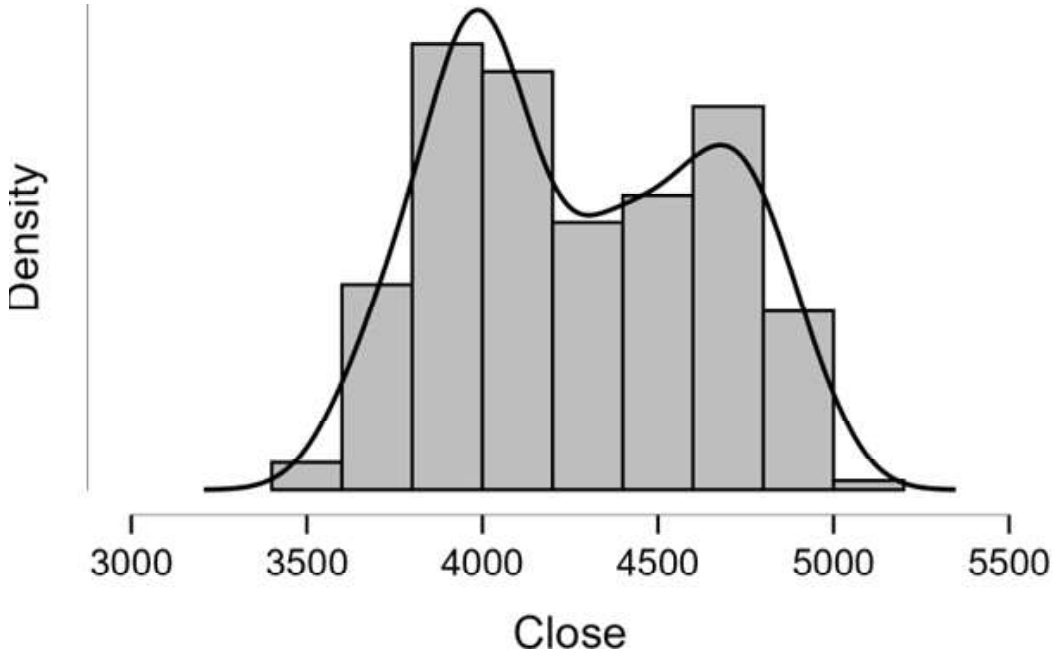
2013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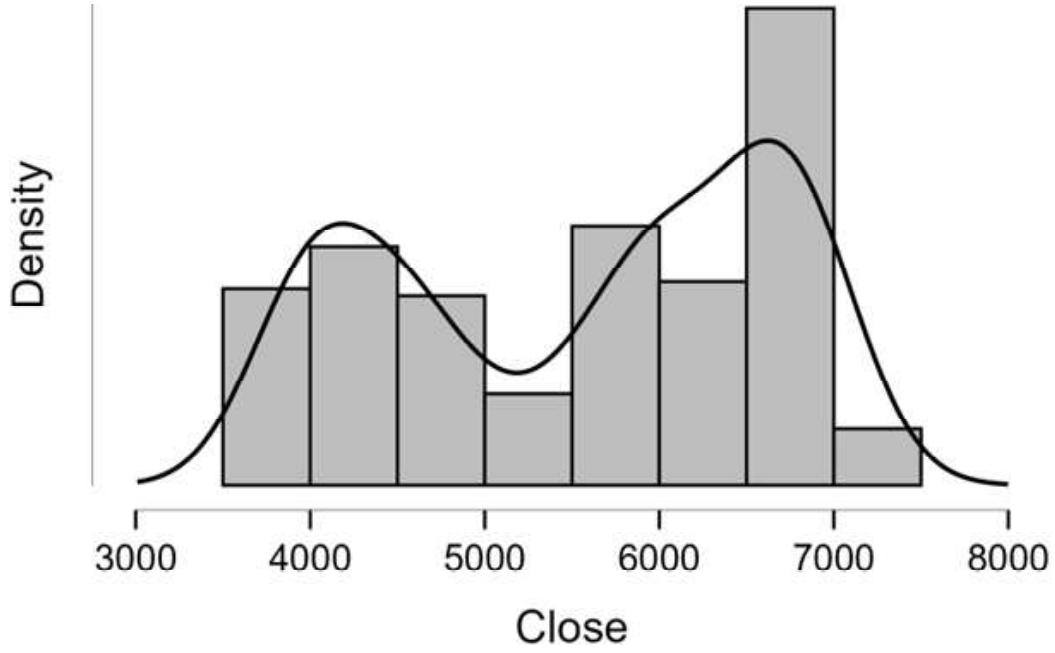
2014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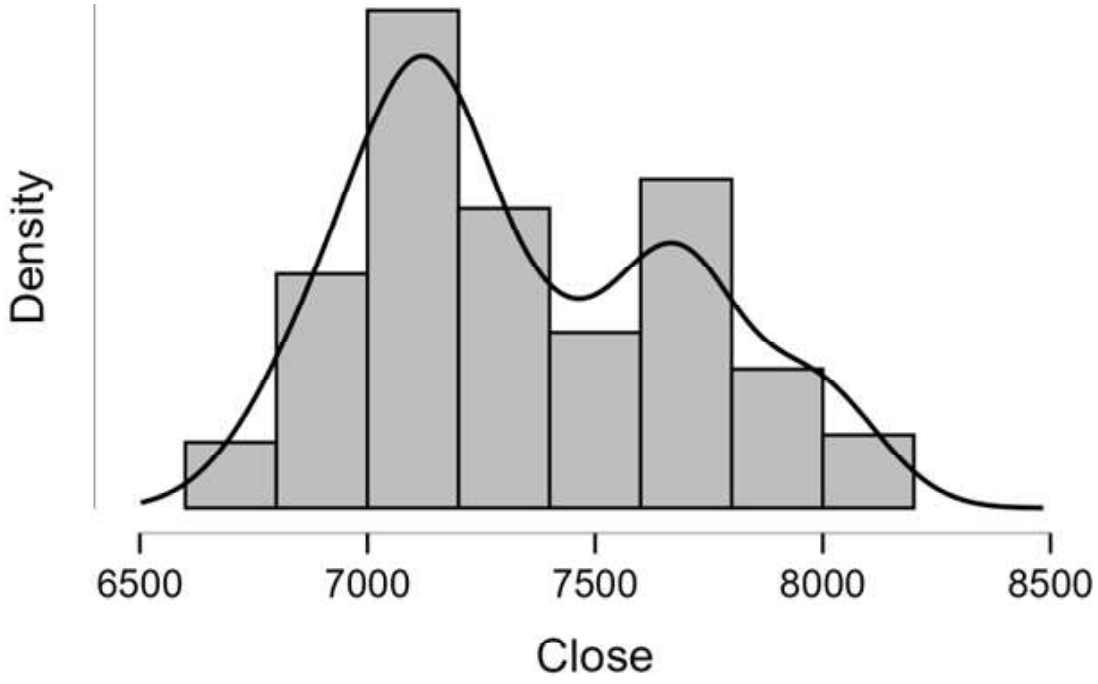
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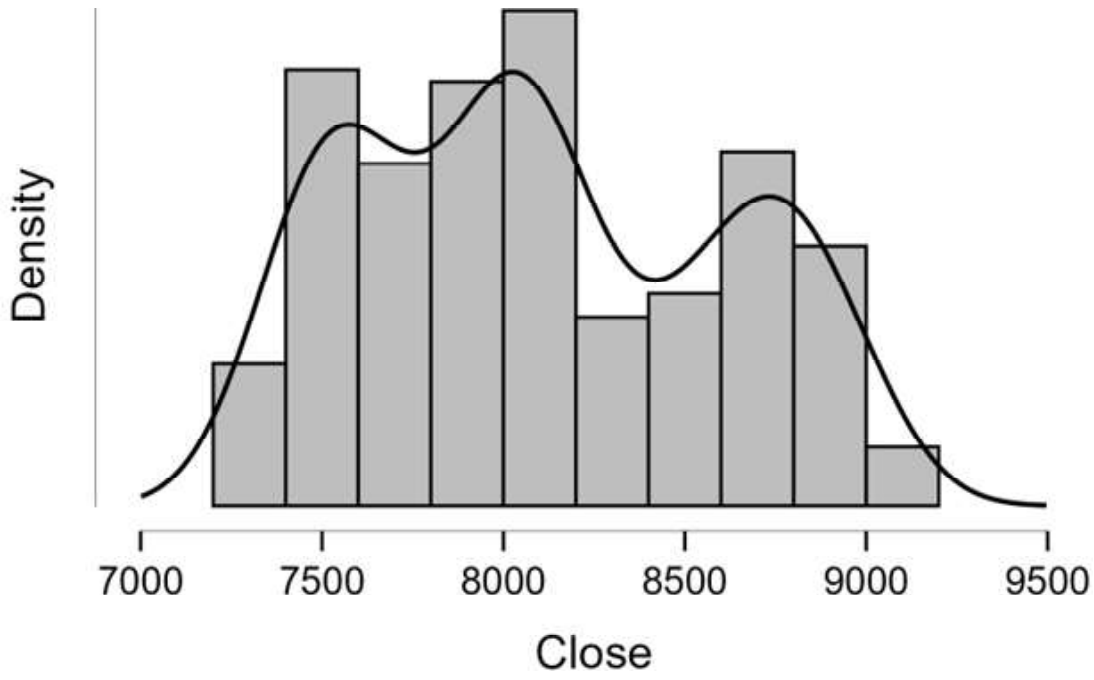
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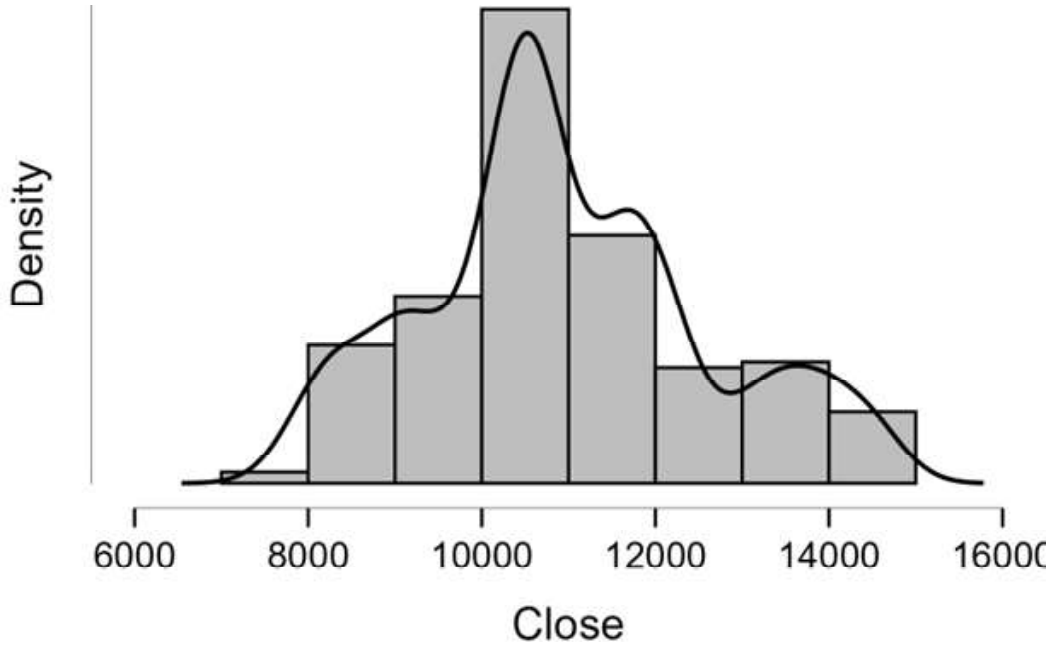
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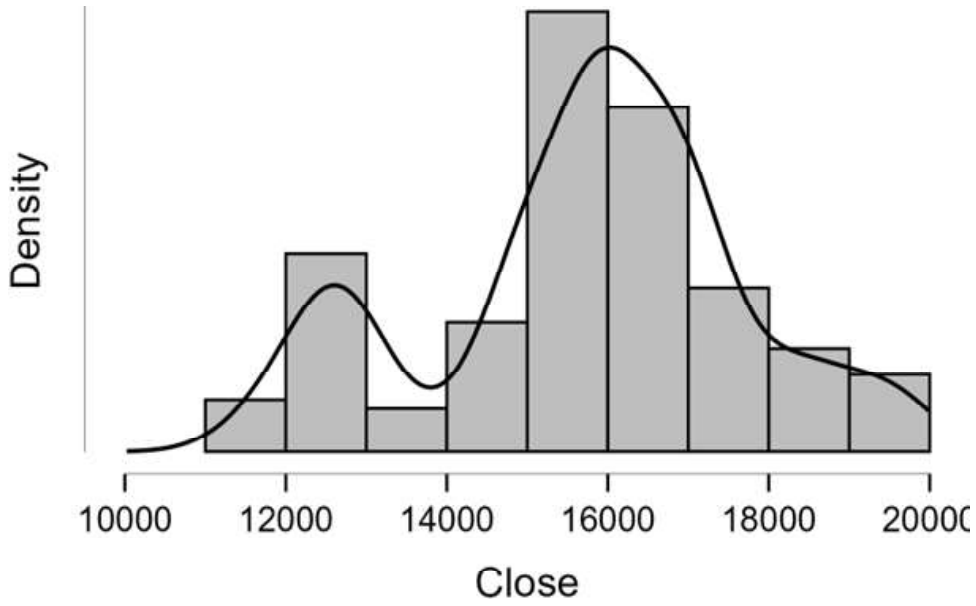
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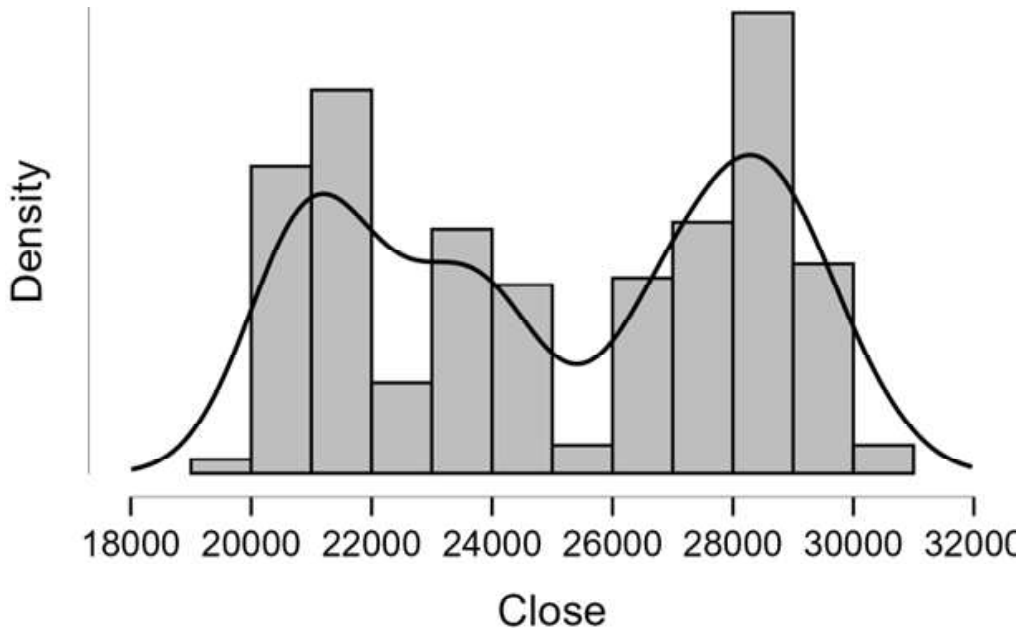
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2022

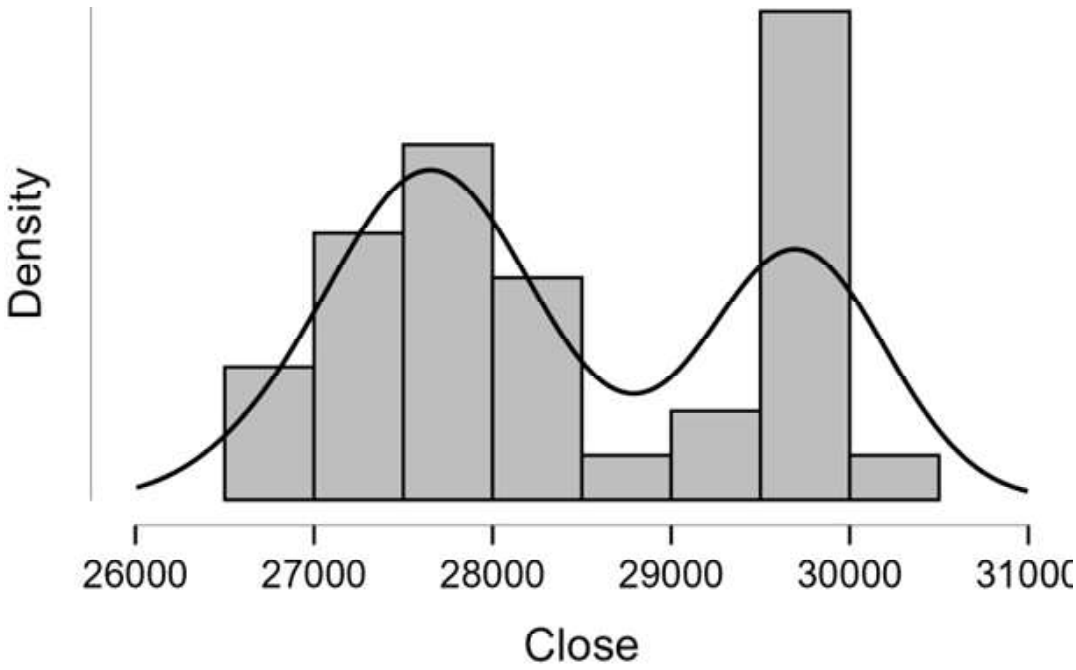

Table 11 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.1002	9.9790	Weibull	-0.7172	1.3944	Weibull
2011	-0.5459	1.8318	Weibull	-0.1125	8.8865	Weibull
2012	-0.2852	3.5068	Weibull	-0.2724	3.6711	Weibull
2013	-0.2851	3.5080	Weibull	-0.4447	2.2489	Weibull
2014	-0.7227	1.3837	Weibull	-0.0173	57.6840	Weibull
2015	-0.1047	9.5499	Weibull	-0.4798	2.0844	Weibull
2016	-0.2300	4.3475	Weibull	-0.5290	1.8904	Weibull
2017	-0.1936	5.1657	Weibull	-0.3911	2.5571	Weibull
2018						
2019						
2020	-0.3615	2.7663	Weibull	-0.2250	4.4449	Weibull
2021	-0.5682	1.7598	Weibull	-0.2156	4.6386	Weibull
2022	-0.0580	17.2337	Weibull	-0.6078	1.6452	Weibull

Source : From researcher's data analysis

Weibull model turned out to be an appropriate model that best suits the behaviour of the maximum and the minimum index variables. Using this, one can calculate the associated probabilities.

Table 12 : Tail index and classification of the Index

	Shape	Scale	Comments based on the tail index
2010	3.900247	2402.5	heavy-tailed and moments of higher order exists
2011	6.039279	3145	heavy-tailed and moments of higher order exists
2012	3.983654	3275.7	heavy-tailed and moments of higher order exists
2013	5.388105	3543.1	heavy-tailed and moments of higher order exists
2014	2.723557	3795.3	heavy-tailed and only mean exists
2015	10.21824	6661.9	heavy-tailed and moments of higher order exists
2016	8.851011	7238	heavy-tailed and moments of higher order exists
2017	2.91865	7729.6	heavy-tailed and only mean exists
2018	-	-	
2019	-	-	
2020	3.098376	11376.41	heavy-tailed and moments of higher order exists
2021	4.433767	19920.61	heavy-tailed and moments of higher order exists
2022	15.83297	26786.1	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

The index values in the above table indicates that the tails are heavy and during the years 2014 and 2017 only the mean exists and no other moments exists. Studying the events and their impact during the years will give one a better understanding of the sector.

Table 13 : Index value for Stable Models

	α	β	Σ	M	Model
2010	2	0	386.7553	3135.3351	Normal
2011	2	0	191.8759	3708.6455	Normal
2012	0.8538	0.0006	132.9285	4210.9960	Stable
2013	2	0	289.2825	4271.7551	Normal
2014	2	0	854.1282	5554.6591	Normal
2015	2	0	268.3461	7348.6472	Normal
2016	2	0	380.4911	8108.0814	Normal
2017	1.998	0	1151.583	10965.875	Stable
2018					
2019					
2020	1.96237	-1	1349.824	15784.64	Stable
2021	2	0	2565.543	25059.611	Normal
2022	2	0	833.7007	28426.14	Normal

Source: From researcher's data analysis

From the above table it very clear that a normal model suits the cumulative index variable for many years. For the years 2017 and 2020 the index value is very clost to 2 and this indicates that normal model will approximately suit the cumulative index variable's behaviour. But for the year 2012 the index value is very low and this indicates that the tails are heavy and the cumulative index has to be modelled only using a stable model. One can study the underlying events during this year and monitor the occurrence of the same again, and take precautionary measures to face the change. It is very evident that the impact of the events on the index during 2012 is high and the same can be avoided in future if appropriate measures are taken.

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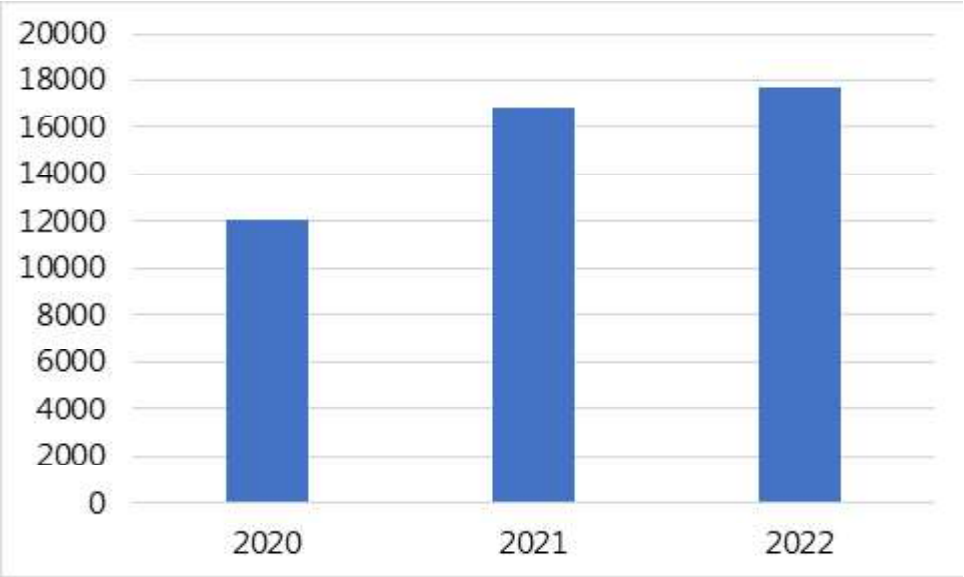
Table 14 : Descriptive Statistics and Test for Normal Probability Model

	2020	2021	2022
Valid	101	246	37
Missing	0	0	0
Mean	12104.633	16857.751	17709.697
Std. Deviation	1422.496	1254.267	448.158
Coefficient of Variation	0.118	0.074	0.025
Skewness	0.526	0.137	-0.082
Std. Error of Skewness	0.240	0.155	0.388
Kurtosis	-1.364	-0.964	-0.976
Std. Error of Kurtosis	0.476	0.309	0.759
Shapiro-Wilk	0.852	0.966	0.968
P-value of Shapiro-Wilk	< .001	< .001	0.346
Minimum	10036.750	14268.200	16776.200
Maximum	14701.450	19324.100	18442.950

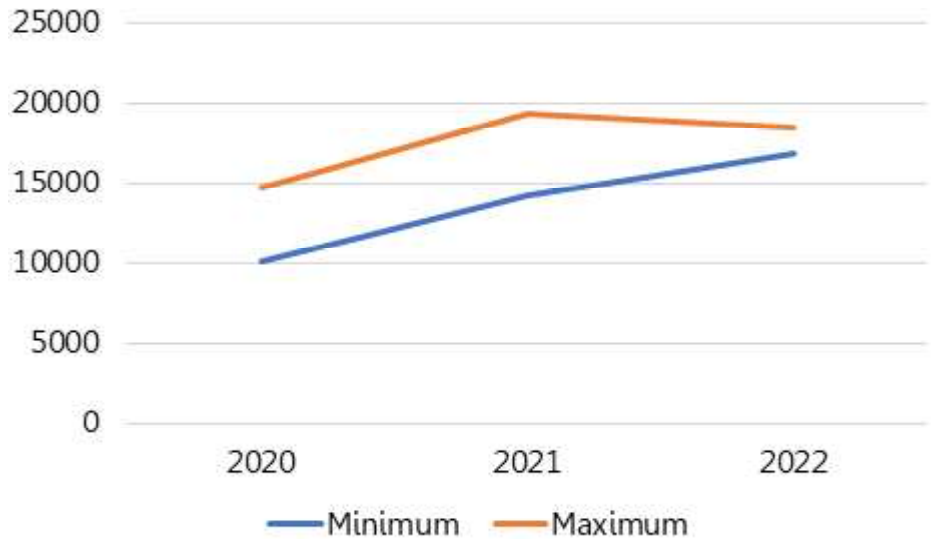
Source: From researcher's data analysis

The above table describes the behaviour of the index over the years. In the year 2022 the normality assumption is satisfied by the data and for the remaining two years the assumption is not satisfied. The graphs below show the increasing trend of the index values over the years. The distribution plots show that the tails are heavy, and the tail index values give the actual behaviour.



Graph 7 : Mean values

Source: From researcher's data analysis



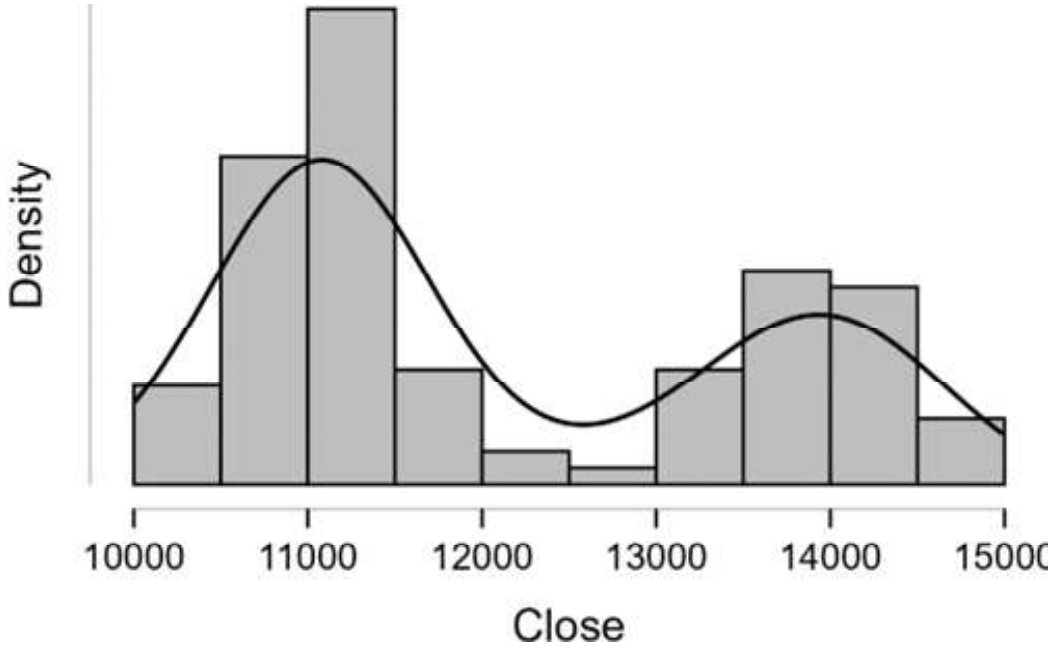
Graph 8 : Maximum and Minimum Index values

Source: From researcher's data analysis

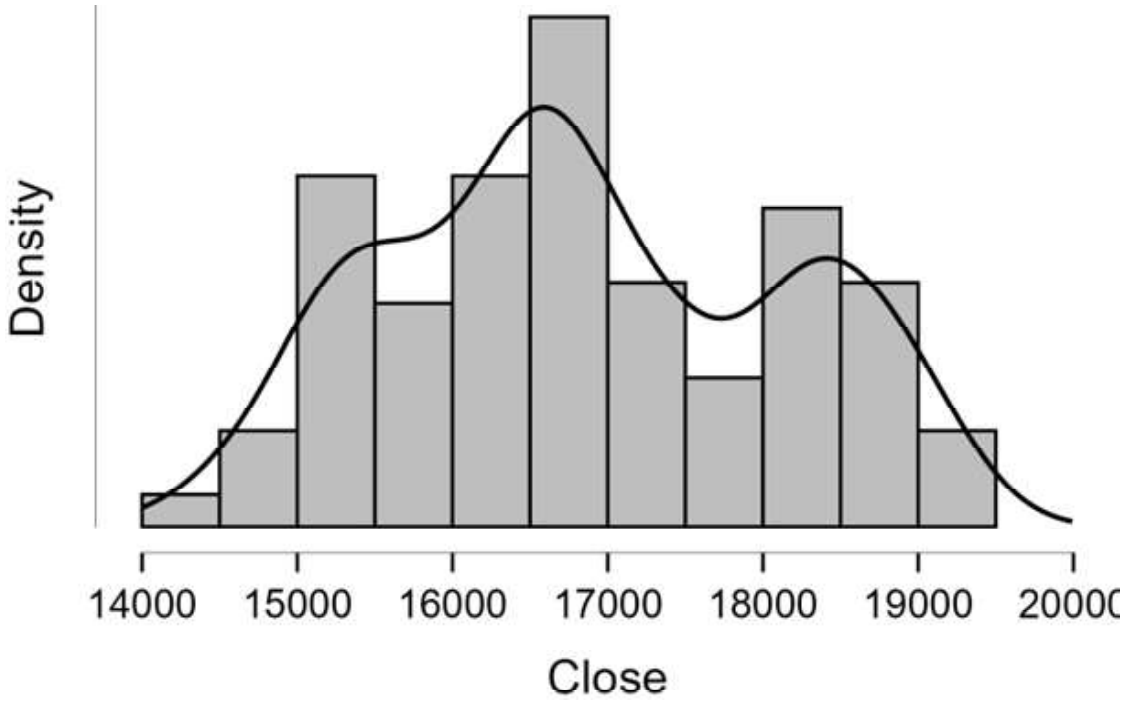
Distribution Plots

Close

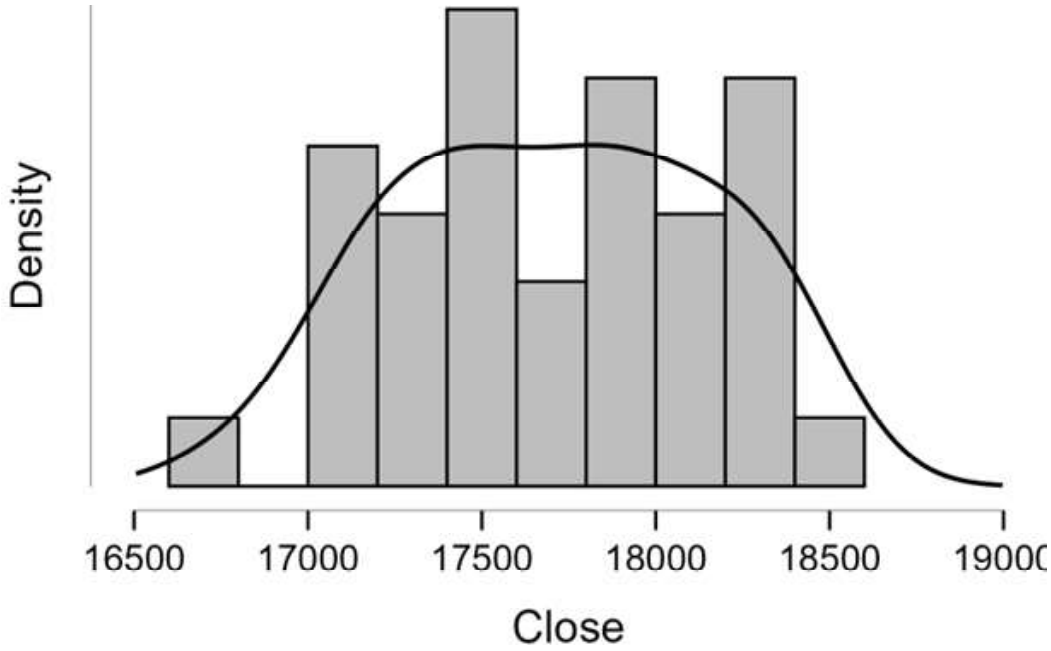
2020



2021



2022



Source: From researcher's data analysis

Table 15 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2020	0.2774	3.6044	Fréchet	-0.5730	1.7452	Weibull
2021	-0.2989	3.3452	Weibull	-0.3913	2.5553	Weibull
2022	-0.4749	2.1058	Weibull	-0.2930	3.4125	Weibull

Source: From researcher's data analysis

Weibull model turns out to be the best model to study the behaviour of the maximum and minimum index variables. For the year 2020 the maximum has to be studied using Fréchet model.

Table 16 : Tail index and classification of the Index

	Shape	Scale	Comments based on the index value
2020	5.357109	10036.75	heavy-tailed and moments of higher order exists
2021	6.005673	14268.2	heavy-tailed and moments of higher order exists
2022	17.20512	16776.2	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

From the above table one can note that the tails are heavy and only the higher order moments exist.

Table 17 : Index value for Stable Models

	α	β	σ	μ	Model
2020	2	0	1076.39	12124.5	Normal
2021	2	0	948.036	16862.4	Normal
2022	2	0	337.085	17708.9	Normal

Source: From researcher's data analysis

Normal model is the appropriate model to study the cumulative index variable. This indicates the information around the index did not impact the cumulative index variable much.

Note: We now present the results of the analysis for other indices and, the interpretation and conclusion on the tail behaviour, extreme index variables behaviour and the cumulative index can be made on similar lines. Hence, we only present the results.

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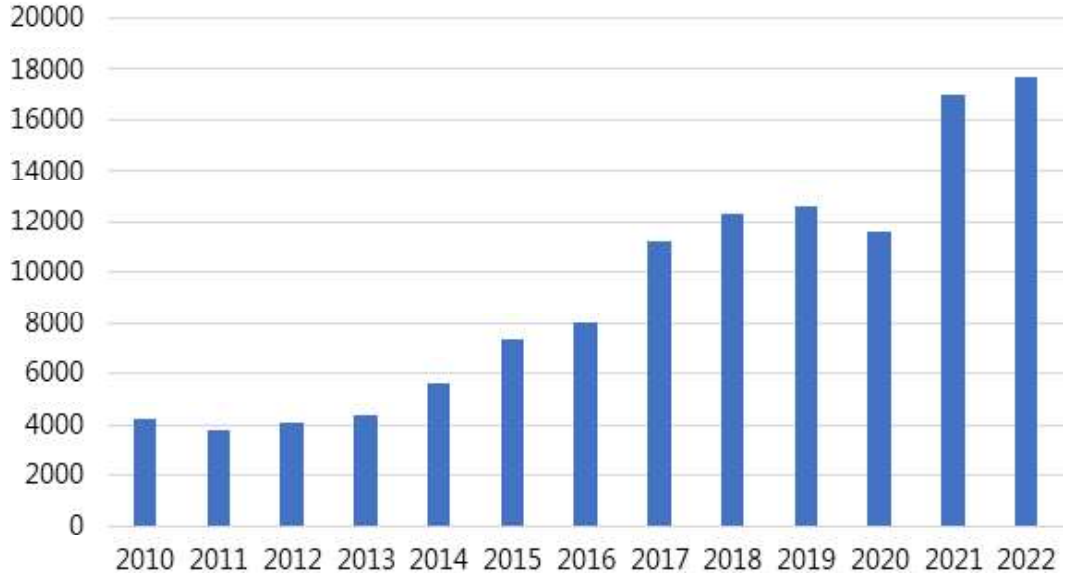
Table 18 : Descriptive Statistics and Test for Normal Probability Model

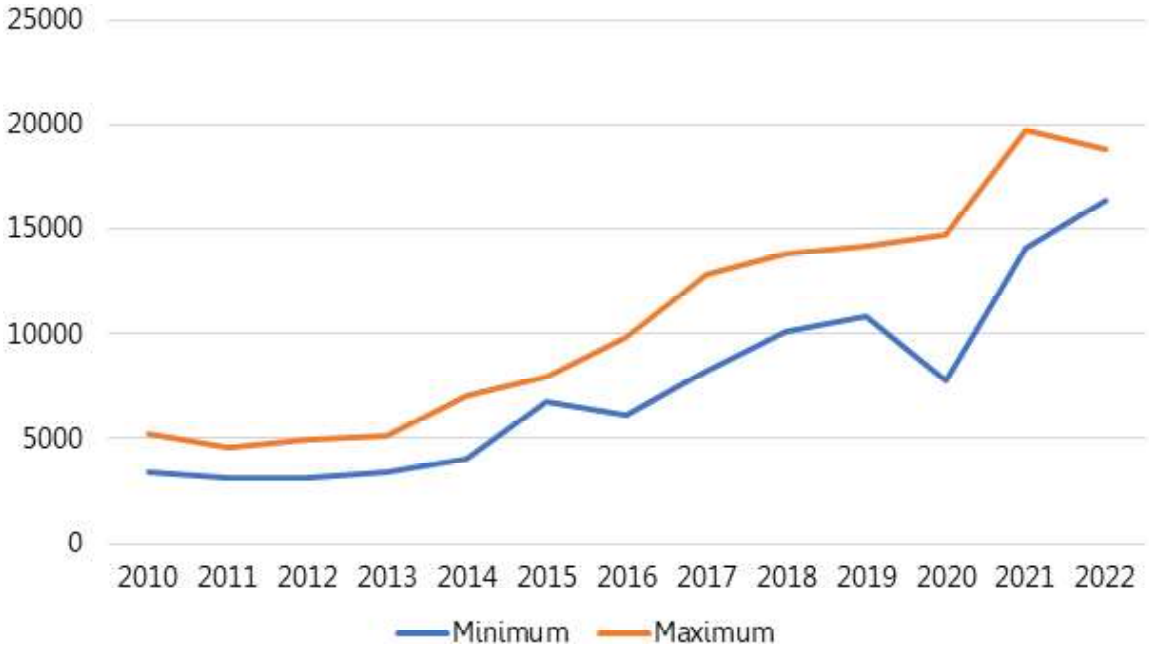
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	246	245	252	248	35
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	4225.675	3825.833	4050.215	4345.743	5590.679	7351.886	8024.309	11237.9	12324.97	12586.28	11578.26	16967.84	17673.8
Std. Deviation	507.263	307.119	374.906	362.723	938.615	262.58	1058.337	1256.882	833.899	809.558	1932.5	1527.62	751.696
Coefficient of Variation	0.12	0.08	0.093	0.083	0.168	0.036	0.132	0.112	0.068	0.064	0.167	0.09	0.043
Skewness	0.314	-0.077	0.483	-0.124	-0.343	-0.113	0.131	-0.729	-0.567	-0.081	0.11	0.211	0.134
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.398
Kurtosis	-1.054	-0.441	0.231	-0.48	-1.326	-0.919	-1.237	-0.504	-0.243	-0.736	-1.142	-1.229	-1.397
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.308	0.778
Shapiro-Wilk	0.946	0.993	0.958	0.989	0.887	0.975	0.945	0.912	0.955	0.981	0.926	0.939	0.927
P-value of Shapiro-Wilk	< .001	0.253	< .001	0.058	< .001	< .001	< .001	< .001	< .001	0.002	< .001	< .001	0.022
Minimum	3421.05	3136.21	3125.56	3423.54	4035.89	6776.14	6156.27	8224.69	10157.51	10838.26	7790.56	14061.57	16375.52
Maximum	5251.32	4601.52	4963.33	5118.55	7002.94	7973.71	9816.56	12859.09	13784.31	14235.32	14720.11	19709.22	18846.47

Source: From researcher's data analysis



Graph 9 : Mean Values of the Index

Source: From researcher's data analysis

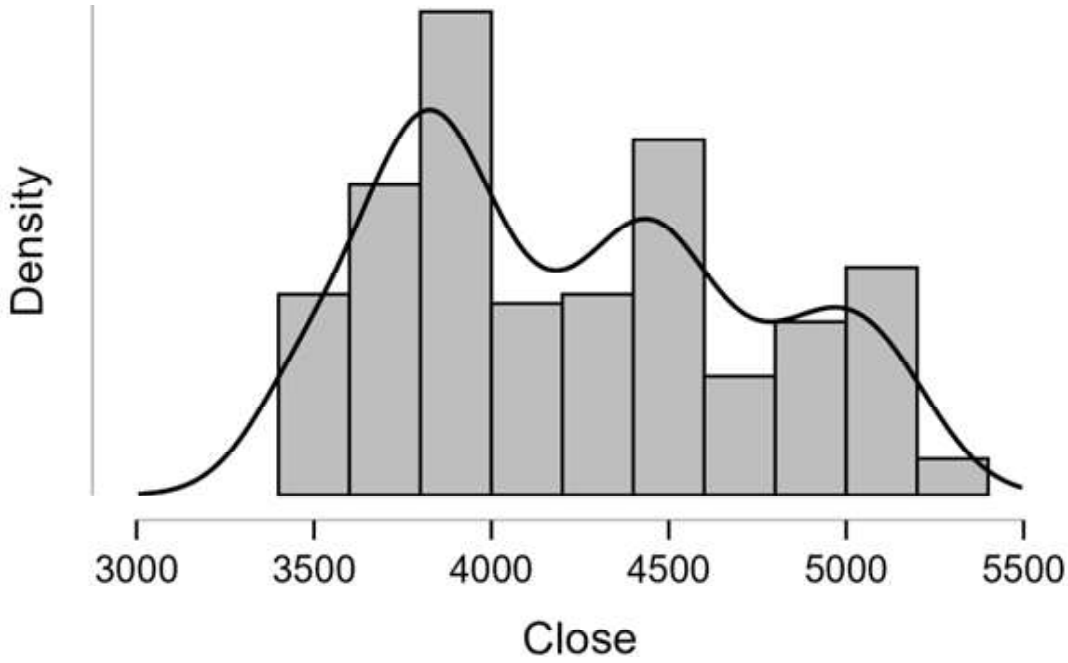


Graph-10 : Maximum and Minimum values of the Index

Source: From researcher's data analysis

Distribution Plots

2010



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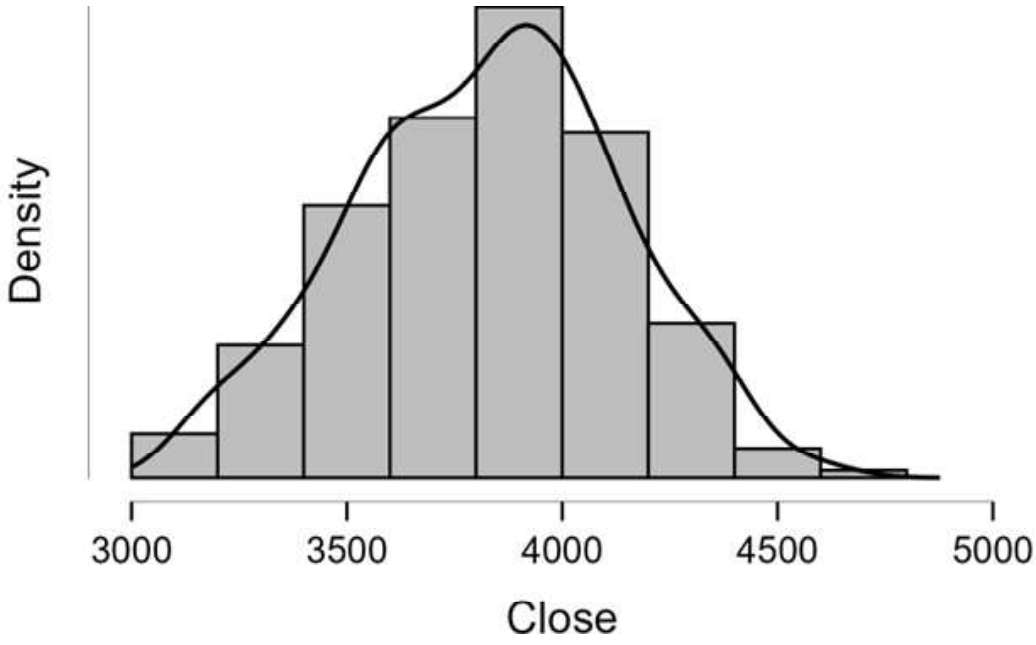

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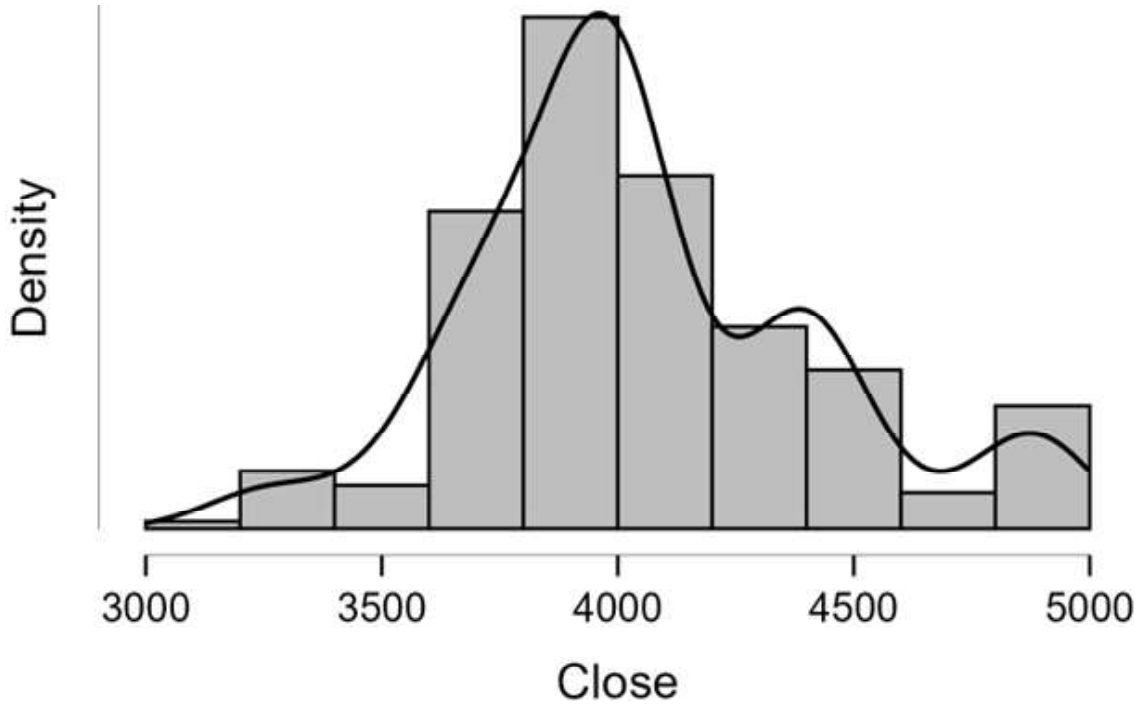
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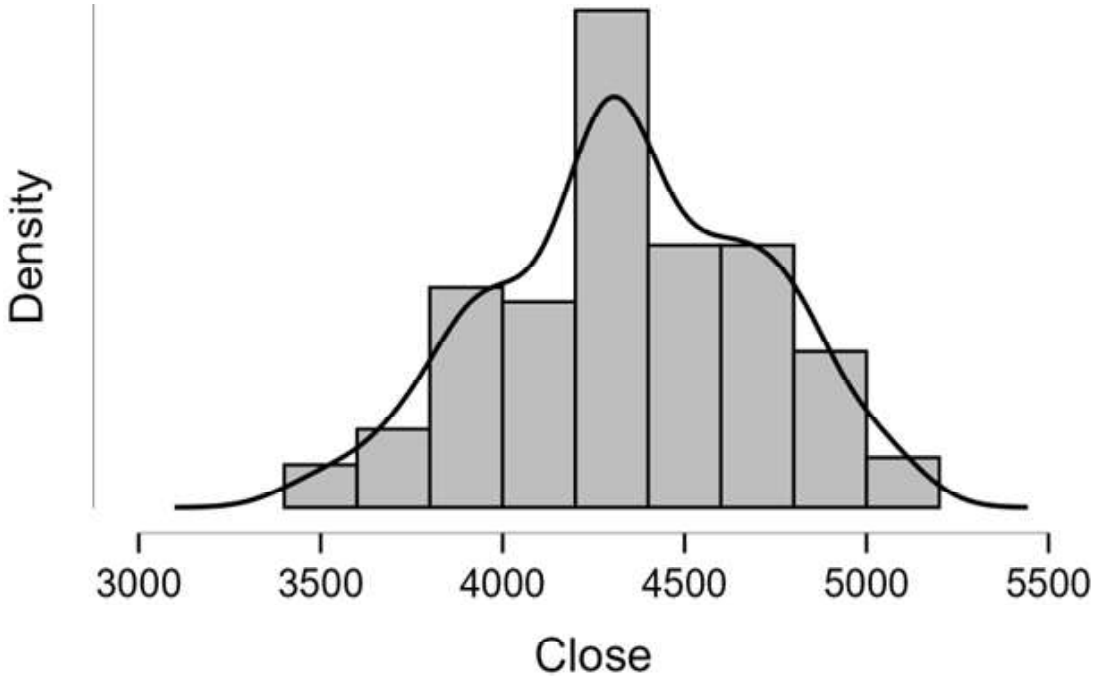
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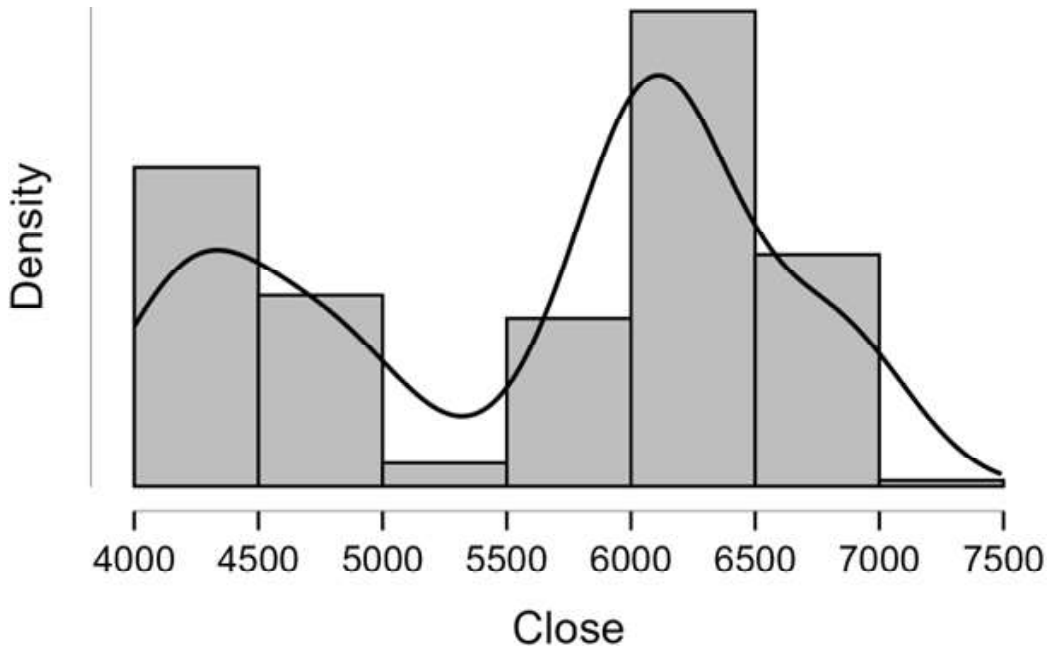
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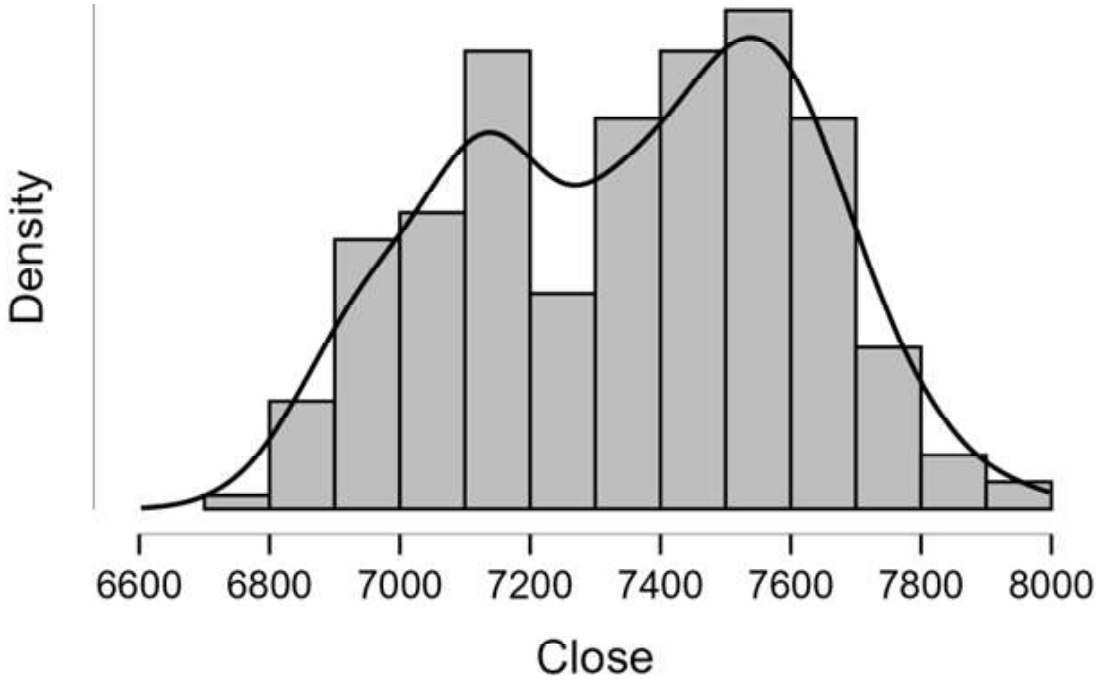
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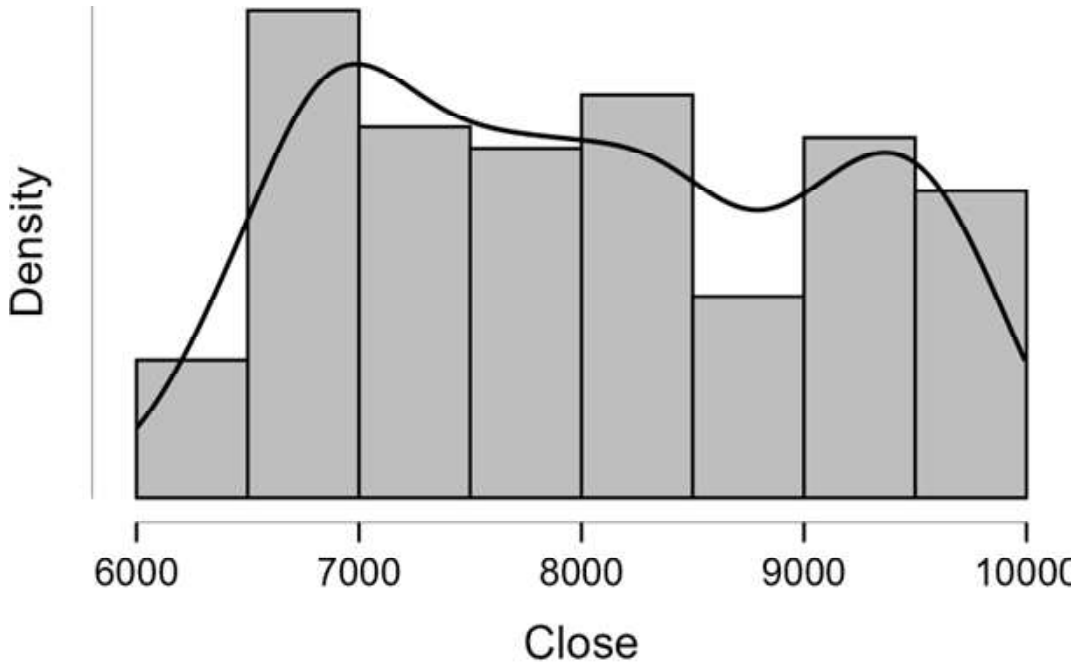
2016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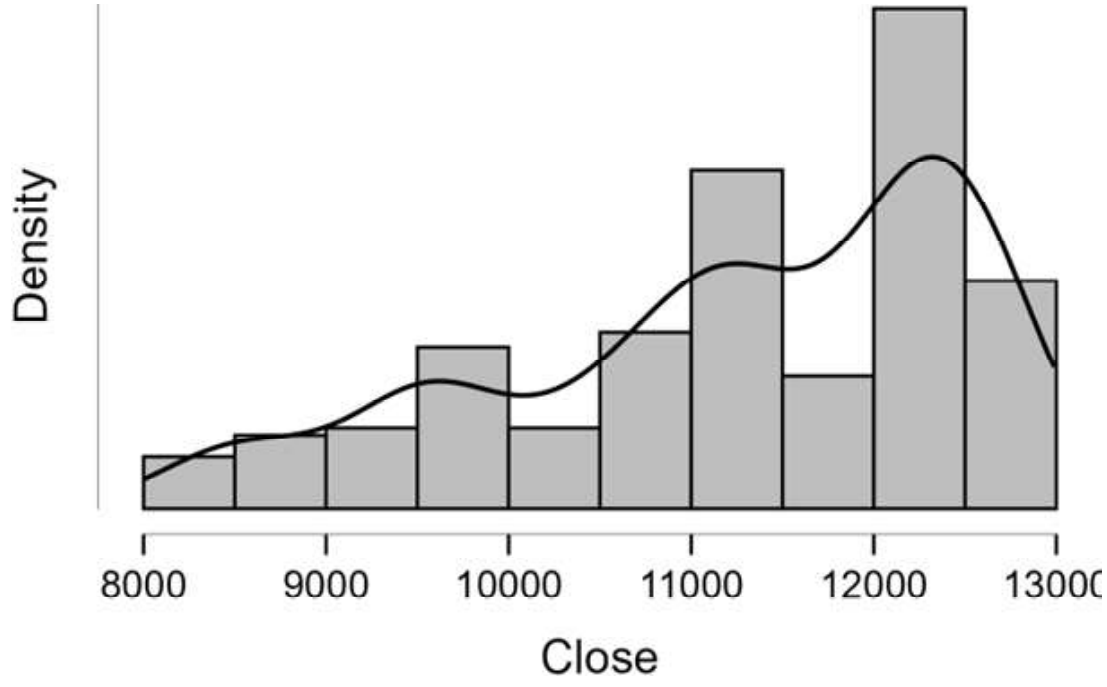
2017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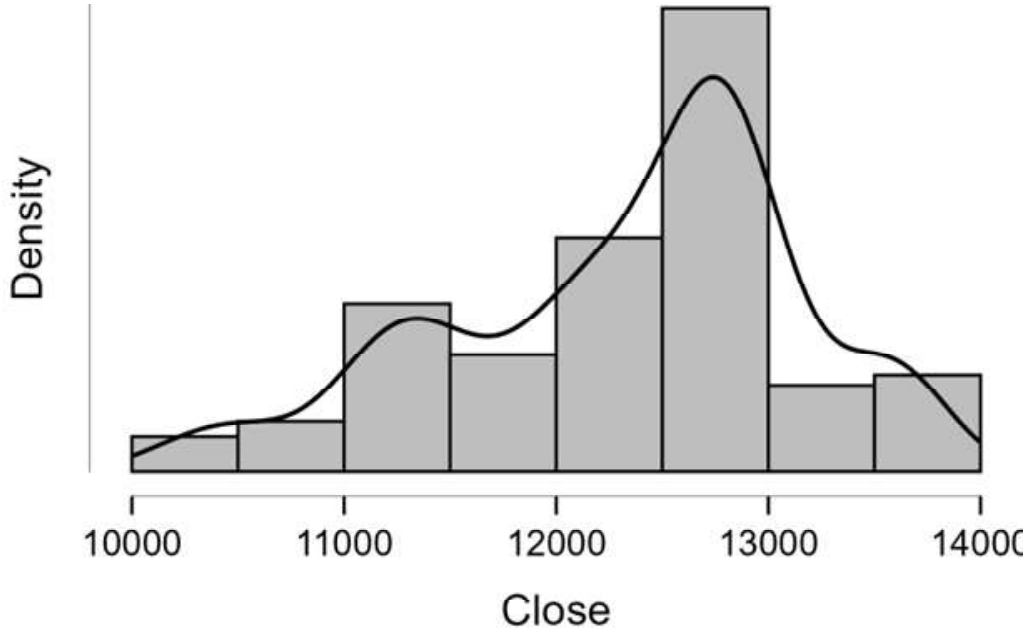
2018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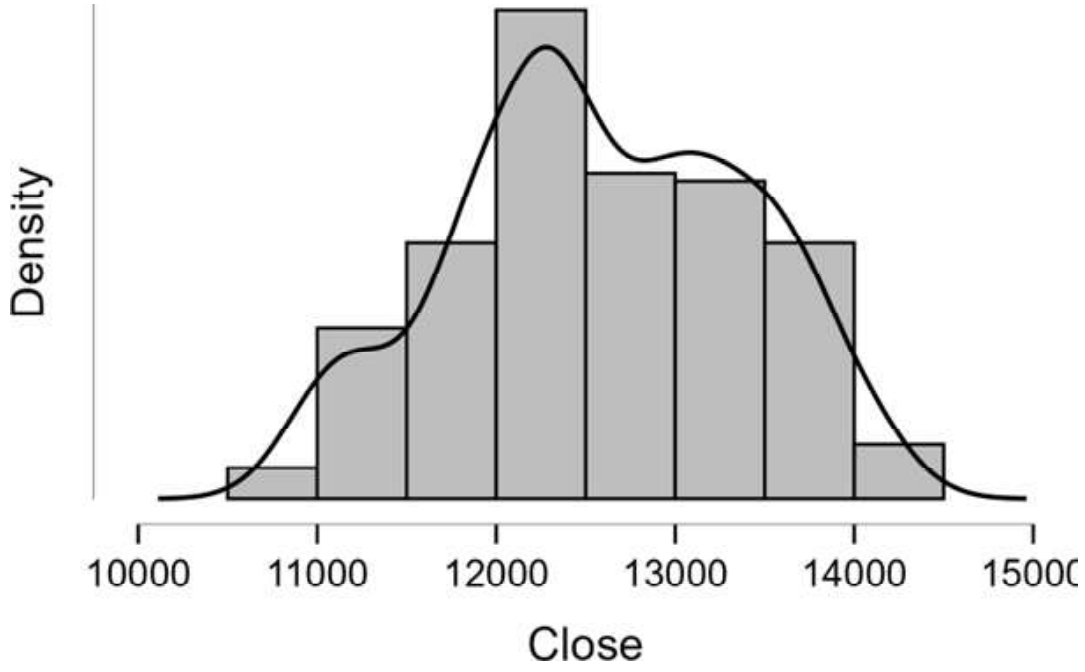
2019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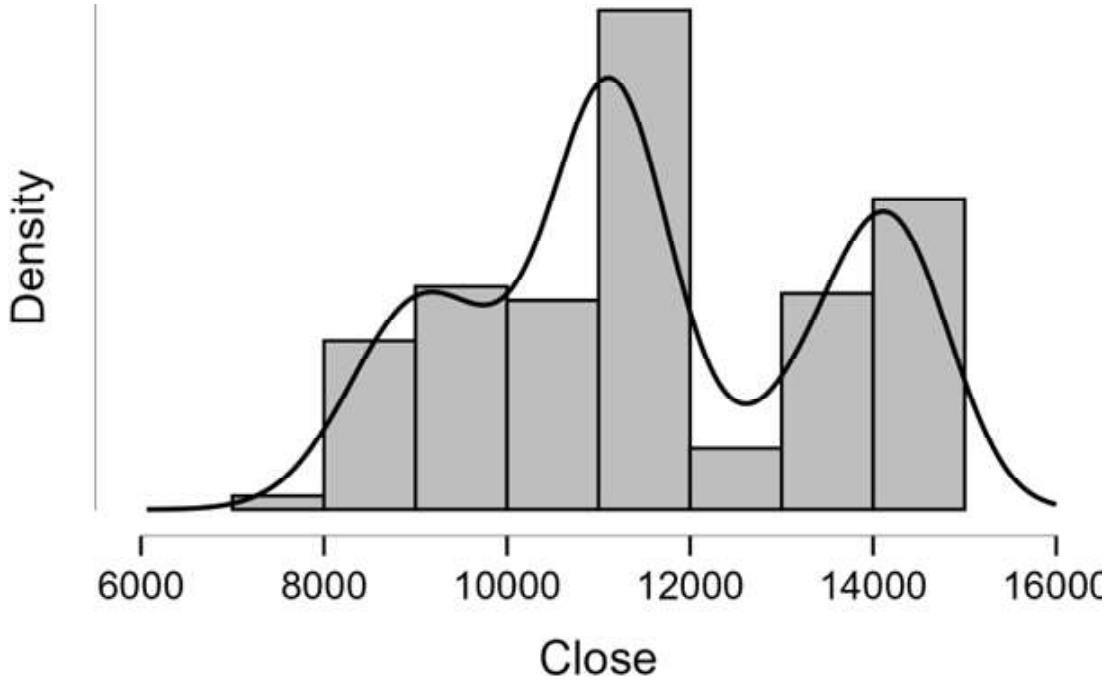
2020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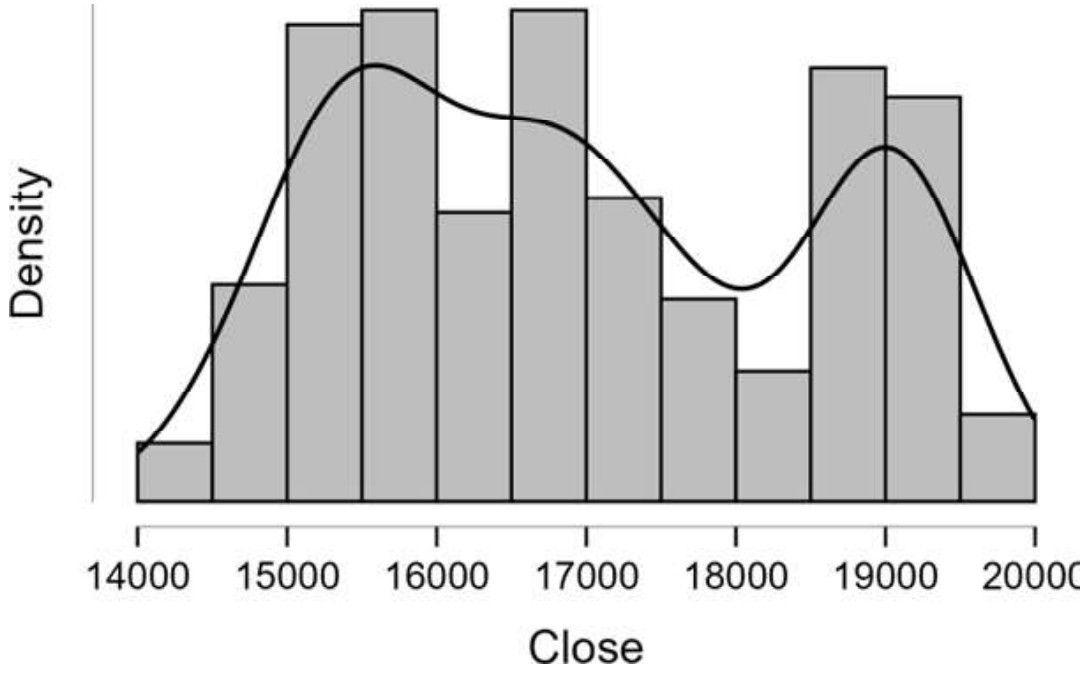
2021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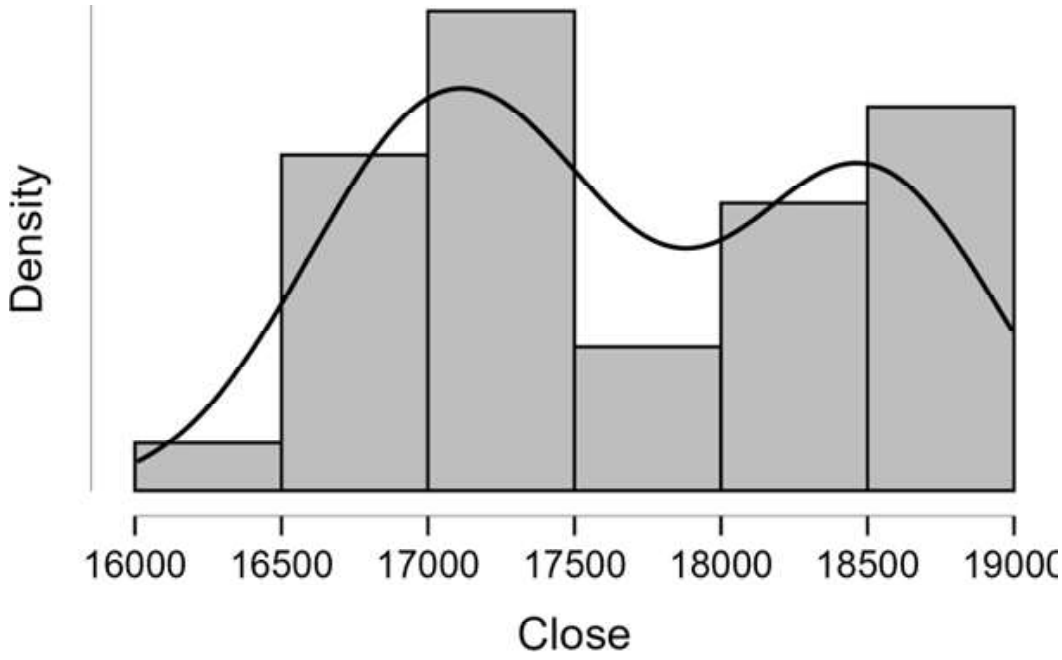
2022



Source: From researcher's data analysis

Table 19 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.1408	7.1025	Weibull	-0.5885	1.6993	Weibull
2011	-0.3039	3.2907	Weibull	-0.2786	3.5895	Weibull
2012	-0.1656	6.0392	Weibull	-0.3496	2.8606	Weibull
2013	-0.3552	2.8150	Weibull	-0.2505	3.9926	Weibull
2014	-0.6672	1.4989	Weibull	-0.0375	26.6890	Weibull
2015	-0.3406	2.9359	Weibull	-0.2943	3.3974	Weibull
2016	-0.3475	2.8780	Weibull	-0.4926	2.0302	Weibull
2017	-0.6791	1.4724	Weibull	0.2419	4.1333	Fréchet
2018	-0.7090	1.4104	Weibull	-0.0841	11.8939	Weibull
2019	-0.3721	2.6871	Weibull	-0.2870	3.4846	Weibull
2020	-0.2338	4.2774	Weibull	-0.4268	2.3431	Weibull
2021	-0.2531	3.9505	Weibull	-0.4226	2.3662	Weibull
2022	-0.4274	2.3396	Weibull	-0.4782	2.0912	Weibull

Source : From researcher's data analysis

Table 20 : Tail index and classification of the Index

	Shape	Scale	Comments based on the tail index
2010	4.827024	3421.05	heavy-tailed and moments of higher order exists
2011	5.038688	3136.21	heavy-tailed and moments of higher order exists
2012	3.864657	3125.56	heavy-tailed and moments of higher order exists
2013	4.192735	3423.54	heavy-tailed and moments of higher order exists
2014	3.167759	4035.89	heavy-tailed and moments of higher order exists
2015	12.17599	6776.14	heavy-tailed and moments of higher order exists
2016	3.843512	6156.27	heavy-tailed and moments of higher order exists
2017	3.225004	8224.69	heavy-tailed and moments of higher order exists
2018	5.15581	10157.51	heavy-tailed and moments of higher order exists
2019	6.68047	10838.26	heavy-tailed and moments of higher order exists
2020	2.578576	7790.56	heavy-tailed and only mean exists
2021	5.358302	14061.57	heavy-tailed and moments of higher order exists
2022	12.23676	16375.52	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 21 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	384.108	4229.7822	Normal
2011	2	0	223.368	3825.155	Normal
2012	1.8534	0.8763	243.8161	4008.3339	Stable
2013	2	0	264.711	4344.6601	Normal
2014	2	0	721.38	5582.2414	Normal
2015	2	0	198.509	7351.0744	Normal
2016	2	0	816.646	8027.8452	Normal
2017	1.96579	-1	875.287	11255.71	Stable
2018	1.9699	-1	580.024	12337.151	Stable
2019	2	0	602.868	12584.748	Normal
2020	2	0	1479.32	11584.261	Normal
2021	2	0	1175.45	16976.196	Normal
2022	2	0	578.572	17676.283	Normal

Source: From researcher's data analysis

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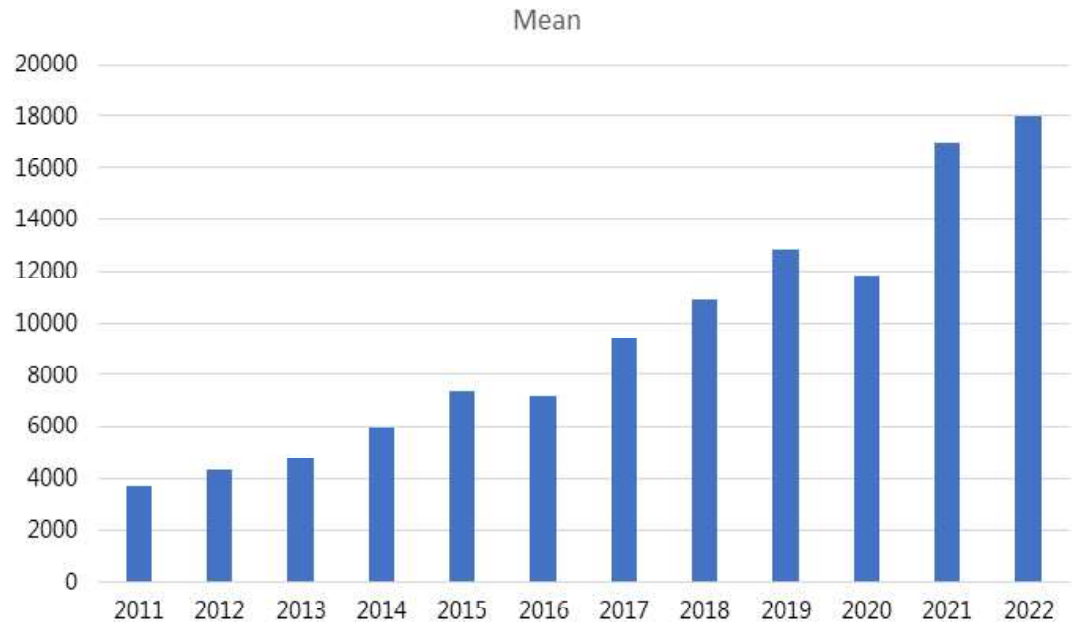
Table 22 : Descriptive Statistics and Test for Normal Probability Model

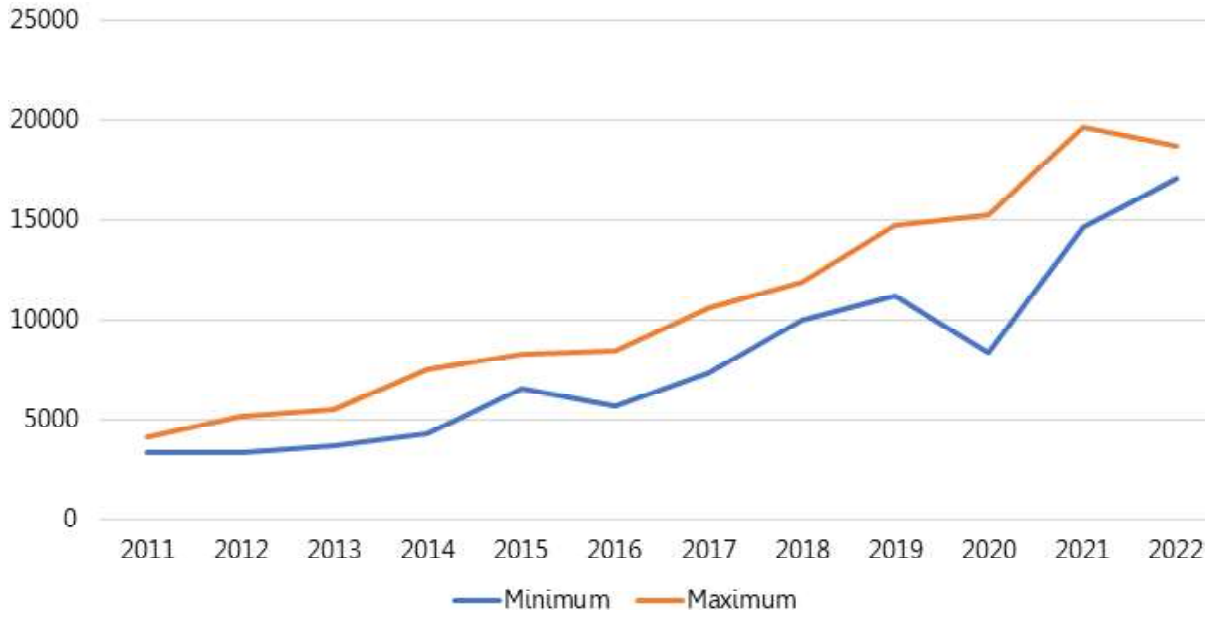
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	78	251	250	244	248	247	248	246	245	252	246	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean	3751.358	4313.486	4743.283	5950.965	7395.411	7212.03	9413.144	10909.06	12788.59	11843.54	16966.75	17966.44
Std. Deviation	210.082	386.999	361.08	924.064	363.155	684.483	898.169	455.161	923.284	1940.146	1173.063	408.04
Coefficient of Variation	0.056	0.09	0.076	0.155	0.049	0.095	0.095	0.042	0.072	0.164	0.069	0.023
Skewness	-0.38	0.385	-0.471	-0.241	0.004	-0.257	-0.715	0.16	0.119	0.252	0.246	0.026
Std. Error of Skewness	0.272	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-1.022	-0.255	-0.082	-1.022	-0.719	-1.049	-0.607	-0.954	-0.881	-1.322	-0.787	-0.848
Std. Error of Kurtosis	0.538	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.944	0.959	0.977	0.932	0.982	0.955	0.91	0.971	0.969	0.906	0.972	0.964
P-value of Shapiro-Wilk	0.002	< .001	< .001	< .001	0.003	< .001	< .001	< .001	< .001	< .001	< .001	0.262
Minimum	3291	3369.9	3714.1	4313.5	6531.2	5689.9	7264.1	9972.75	11148.25	8298.5	14593.3	17059.1
Maximum	4076.5	5146.5	5440.8	7497.1	8269.2	8385.8	10544	11838.1	14679.35	15208	19651.1	18684.75

Source: From researcher's data analysis



Graph 11 : Mean Values of the Index

Source: From researcher's data analysis



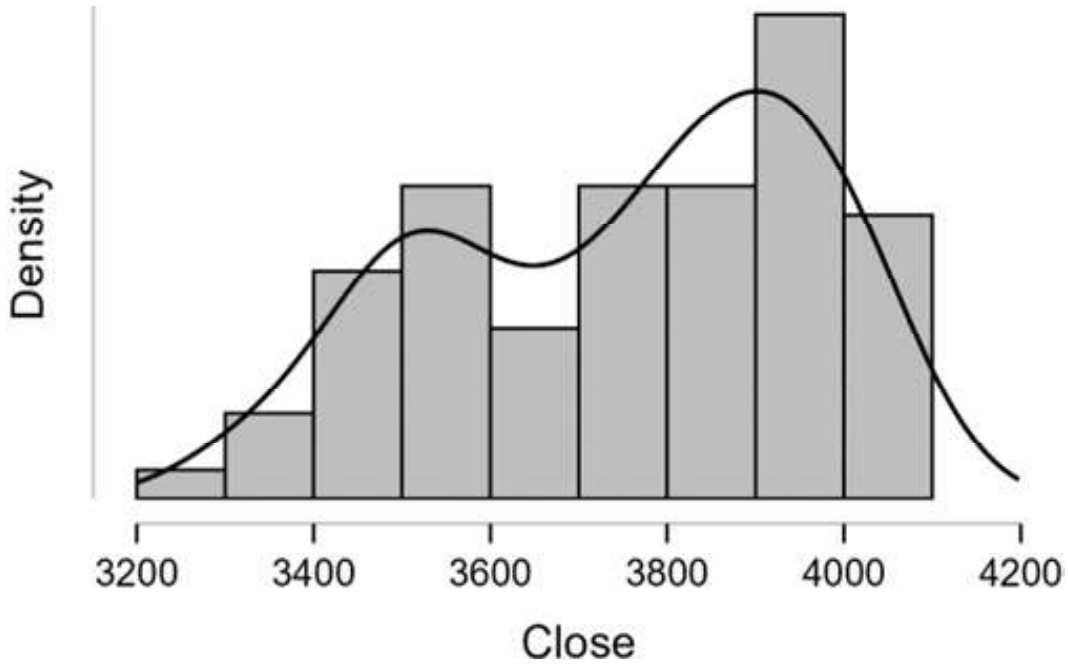
Graph 12 : Maximum and Minimum values of the index

Source: From researcher's data analysis

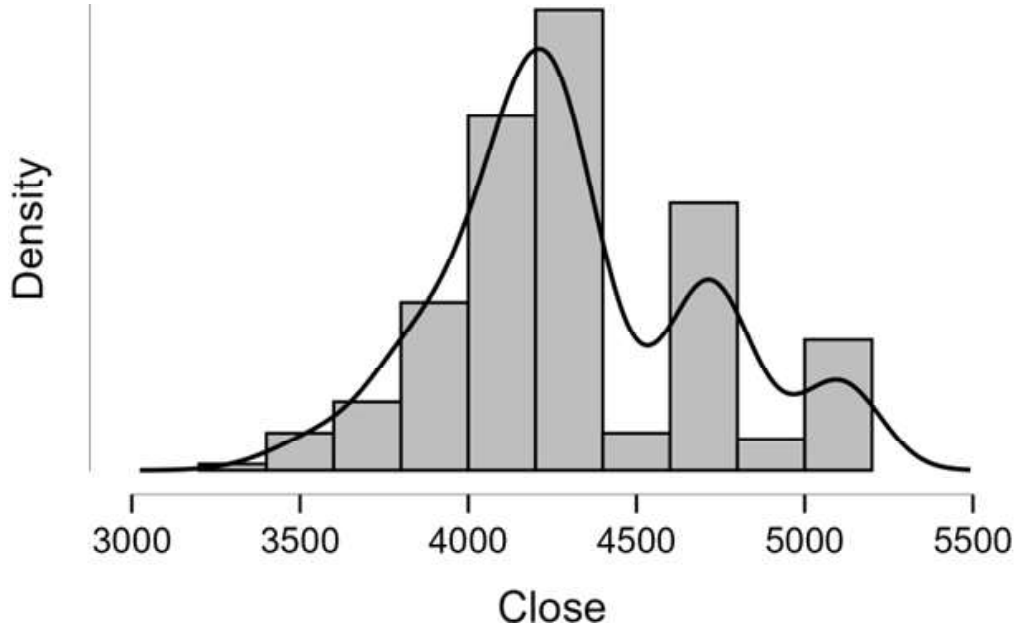
Distribution Plots

Close

2011



2012



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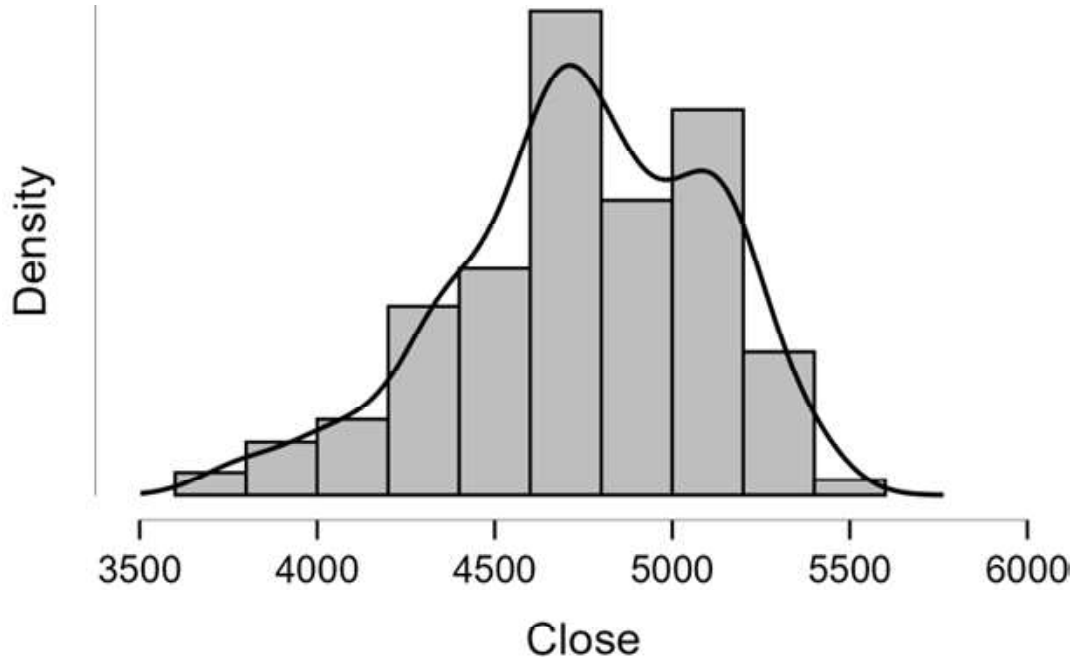
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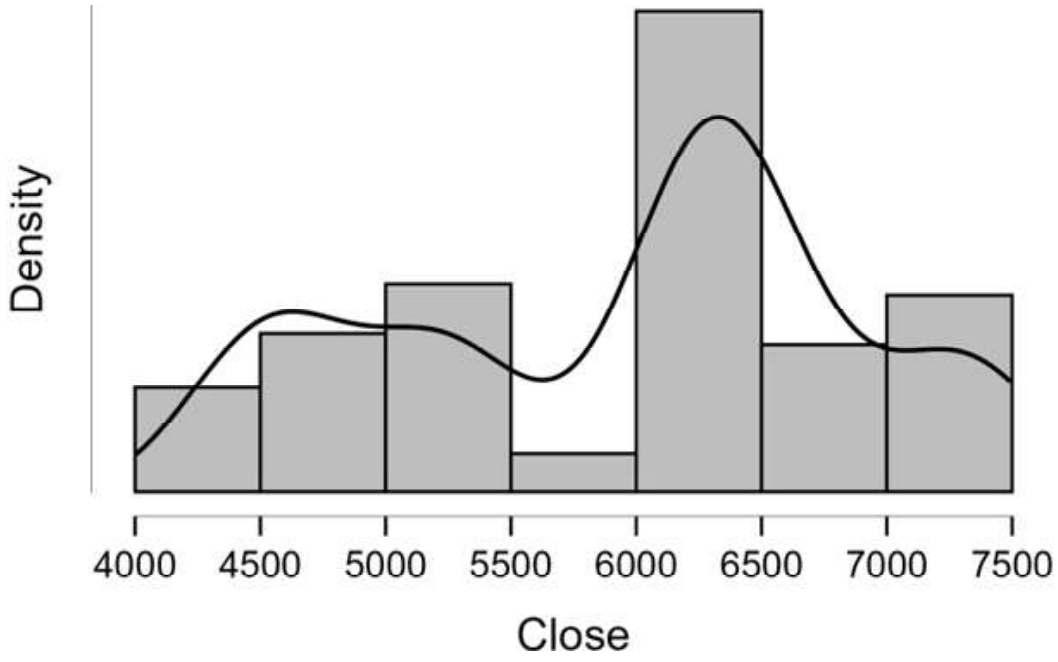
2014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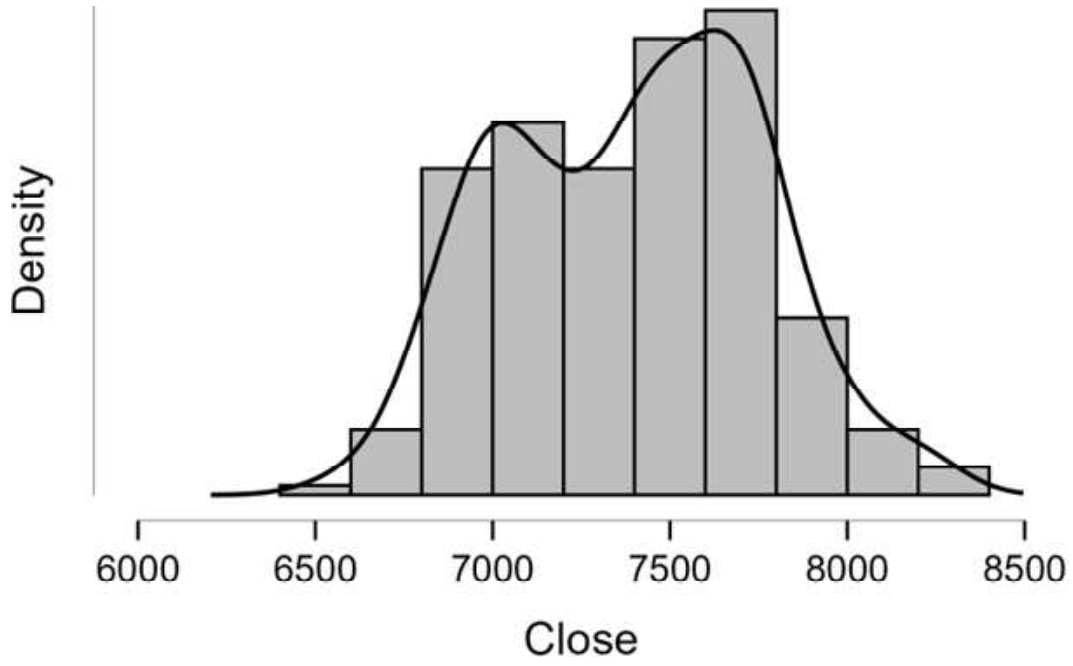
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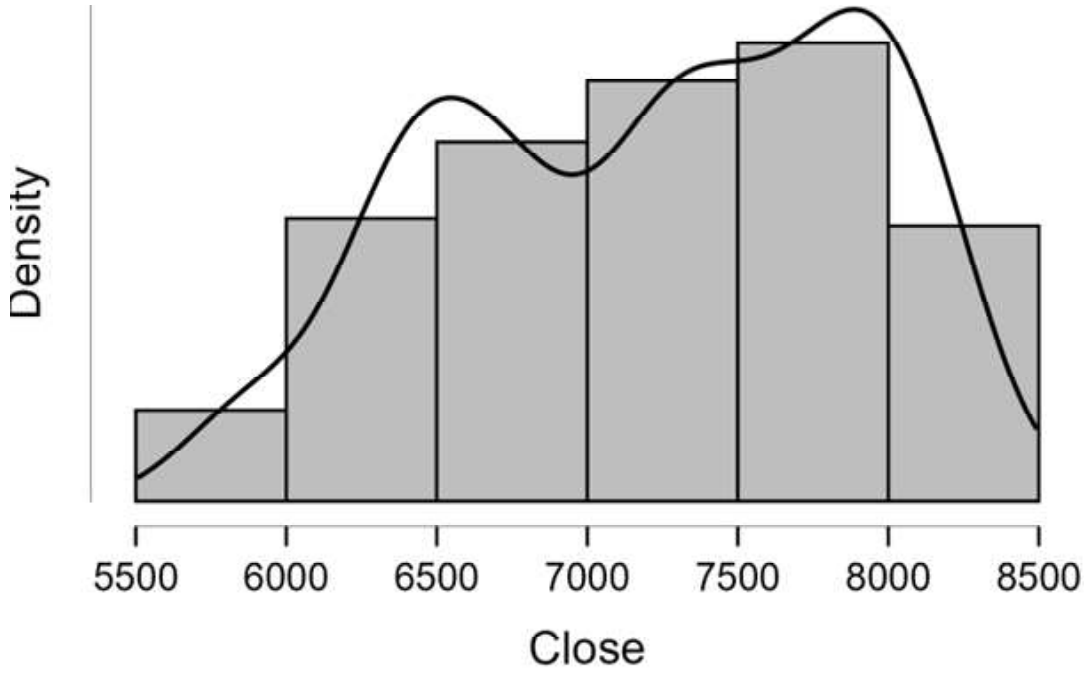
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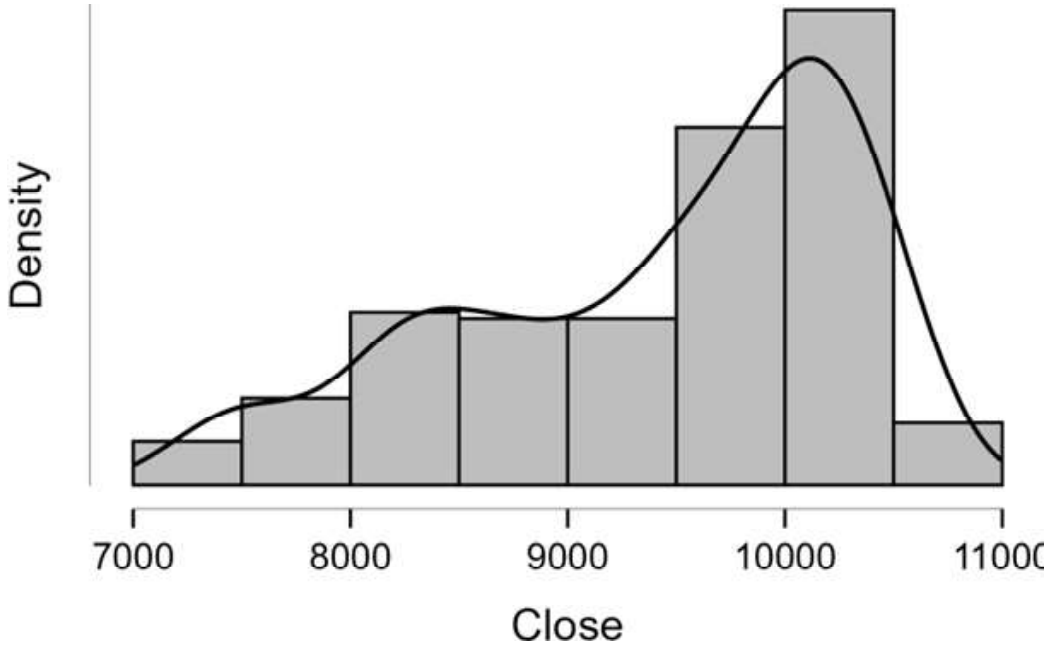
2017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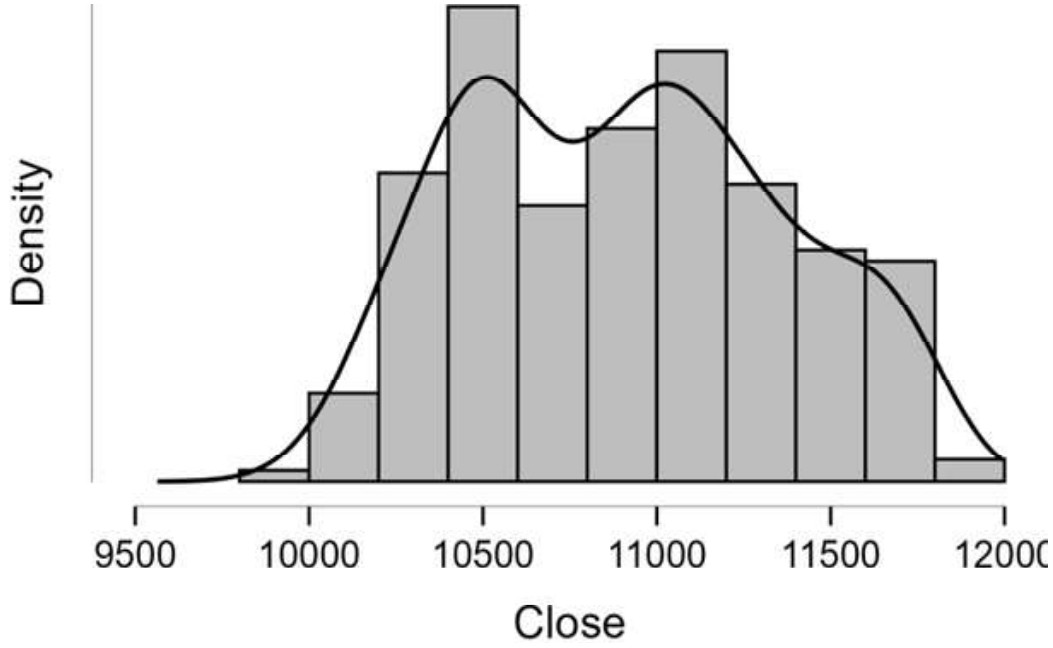
2018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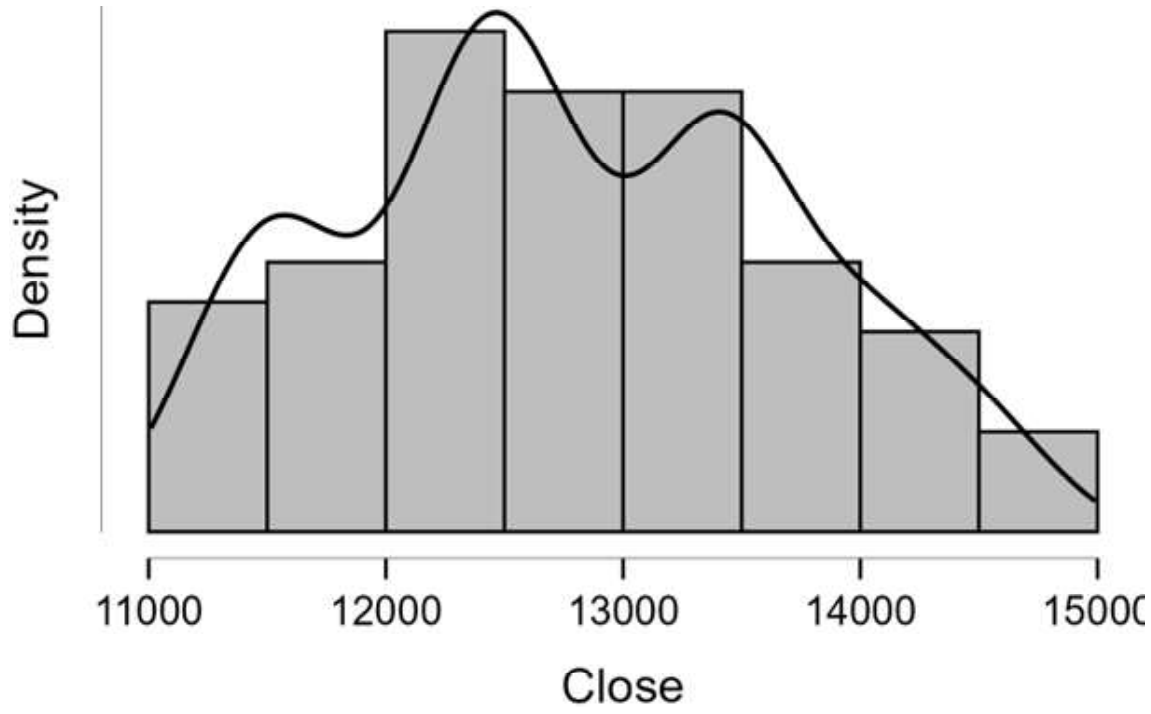
2019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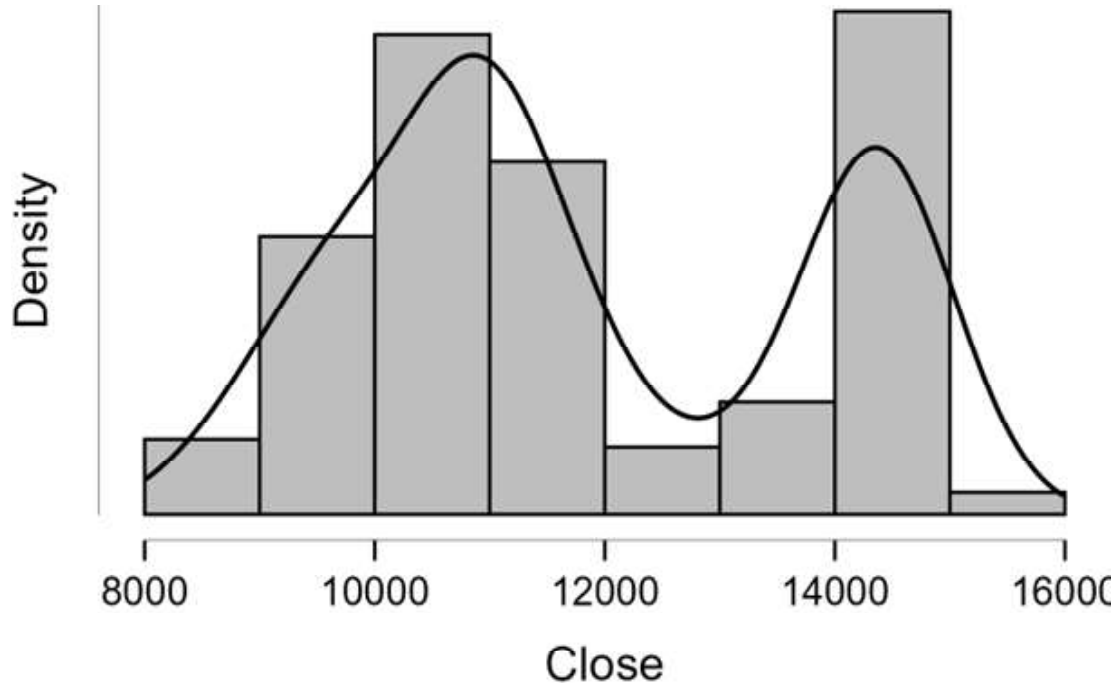
2020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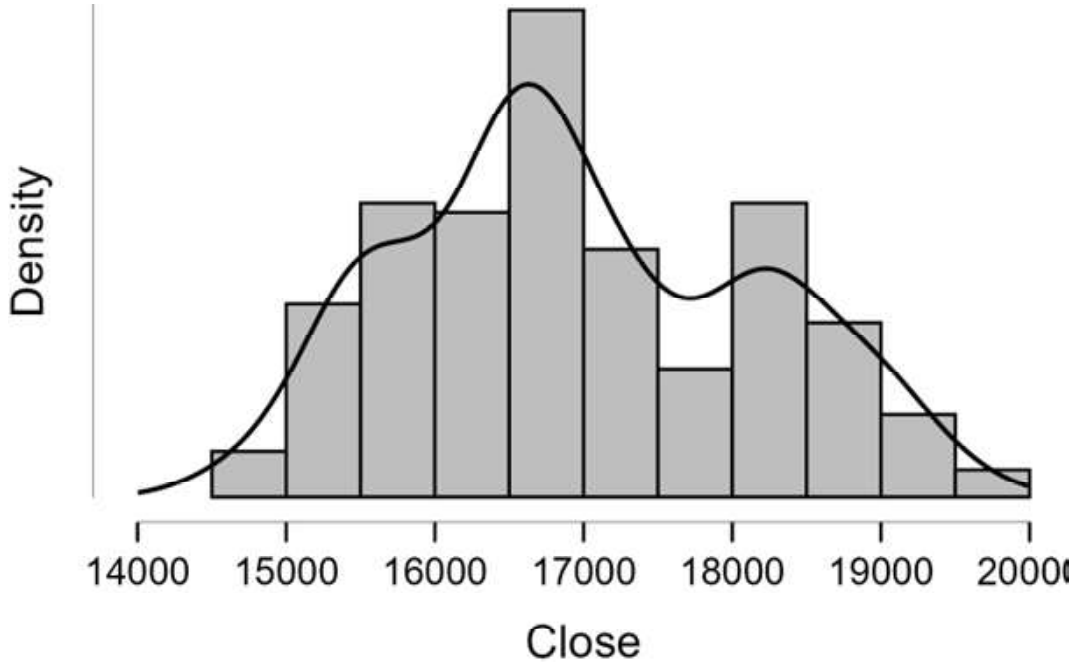
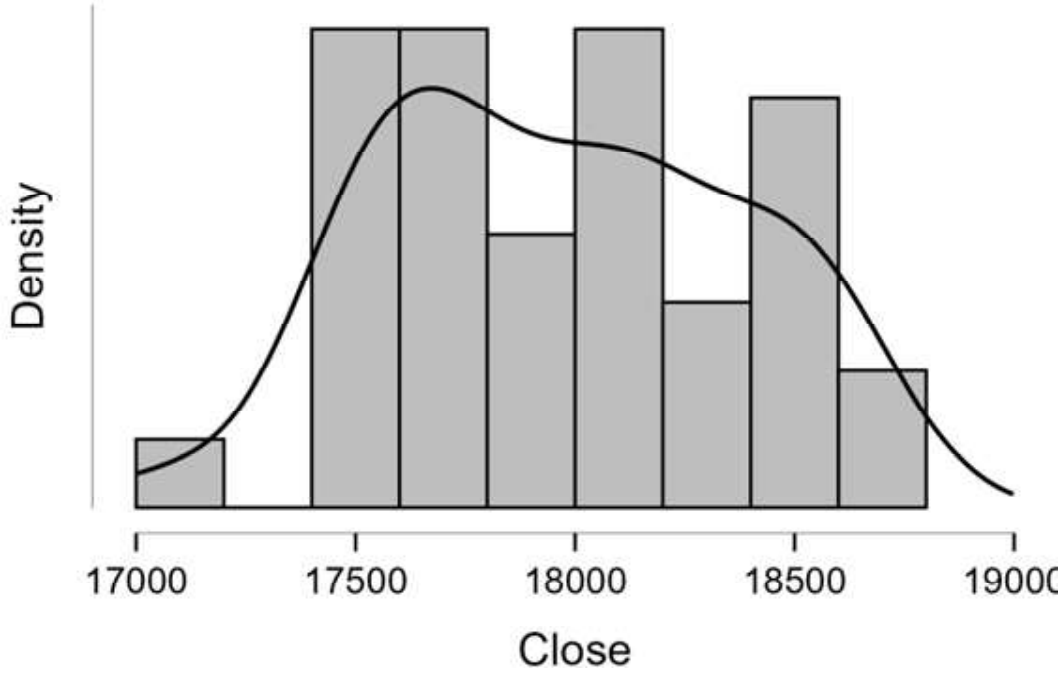
2021



2022



Source: From researcher's data analysis

Table 23 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010						
2011	-0.6196	1.6139	Weibull	-0.0699	14.3009	Weibull
2012	-0.1802	5.5491	Weibull	-0.3536	2.8281	Weibull
2013	-0.4600	2.1737	Weibull	-0.1288	7.7640	Weibull
2014	-0.5178	1.9314	Weibull	-0.2294	4.3592	Weibull
2015	-0.2894	3.4549	Weibull	-0.3206	3.1192	Weibull
2016	-0.5386	1.8565	Weibull	-0.1858	5.3810	Weibull
2017	-0.8221	1.2165	Weibull	0.2608	3.8351	Fréchet
2018	-0.2677	3.7354	Weibull	-0.4207	2.3770	Weibull
2019	-0.2806	3.5633	Weibull	-0.4444	2.2501	Weibull
2020	-0.1989	5.0288	Weibull	-0.4949	2.0206	Weibull
2021	-0.2170	4.6074	Weibull	-0.4120	2.4270	Weibull
2022	-0.3801	2.6306	Weibull	-0.2983	3.3519	Weibull

Source: From researcher's data analysis

Table 24 : Tail index and classification of the Index

	Shape	Scale	
2010	-	-	heavy-tailed and moments of higher order exists
2011	7.415125	3291	heavy-tailed and moments of higher order exists
2012	4.055576	3369.9	heavy-tailed and moments of higher order exists
2013	4.076178	3714.1	heavy-tailed and moments of higher order exists
2014	3.185543	4313.5	heavy-tailed and moments of higher order exists
2015	8.005179	6531.2	heavy-tailed and moments of higher order exists
2016	4.237868	5689.9	heavy-tailed and moments of higher order exists
2017	3.853543	7264.1	heavy-tailed and moments of higher order exists
2018	11.08416	9972.75	heavy-tailed and moments of higher order exists
2019	7.314001	11148.25	heavy-tailed and moments of higher order exists
2020	2.877718	8298.5	heavy-tailed and only mean exists
2021	6.64096	14593.3	heavy-tailed and moments of higher order exists
2022	17.96191	17059.1	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 25 : Index value for Stable Models

	α	β	σ	μ	Model
2010					
2011	2	0	157.8998	3749.3515	Normal
2012	1.9830	0.0000	271.0421	4318.1599	Stable
2013	1.9915	0	253.612855	4738.78051	Stable
2014	2	0	697.9285	5944.9203	Normal
2015	2	0	271.0894	7395.2944	Normal
2016	**2**	0	520.7326	7207.6855	Normal
2017	1.98744	0	633.475458	9393.966519	Stable
2018	2	0	344.164	10910.896	Normal
2019	2	0	694.7839	12791.2863	Normal
2020	2	0	1498.285	11856.486	Normal
2021	2	0	872.3648	16974.4233	Normal
2022	2	0	304.7837	17966.9253	Normal

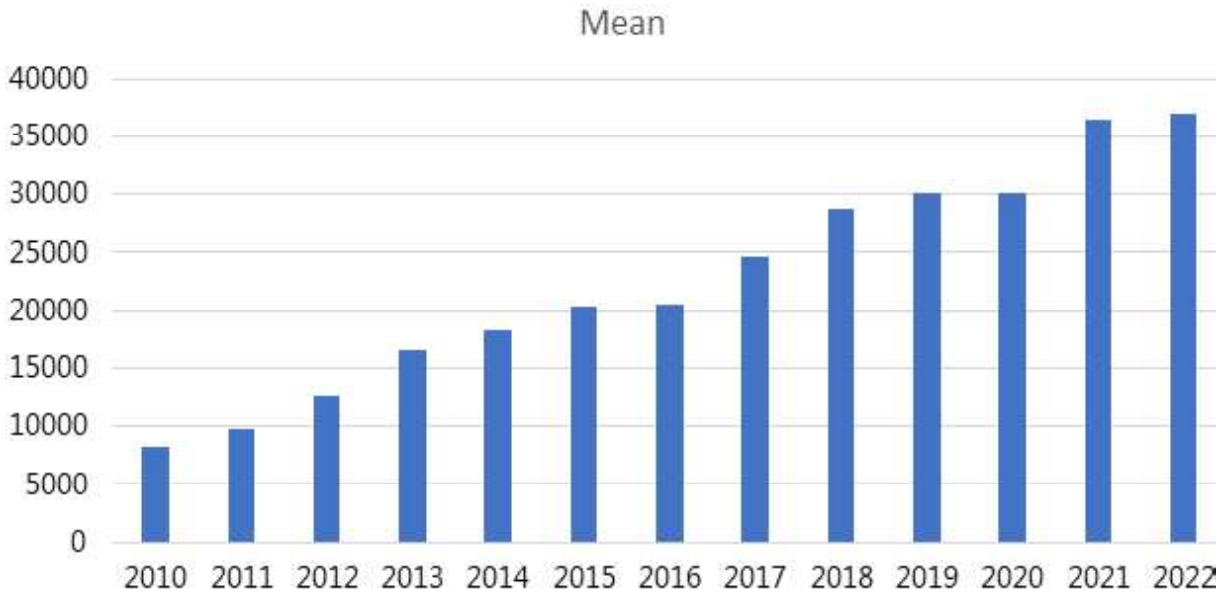
Source: From researcher's data analysis

NIFTY FMCG

Table 26 : Descriptive Statistics and Test for Normal Probability Model

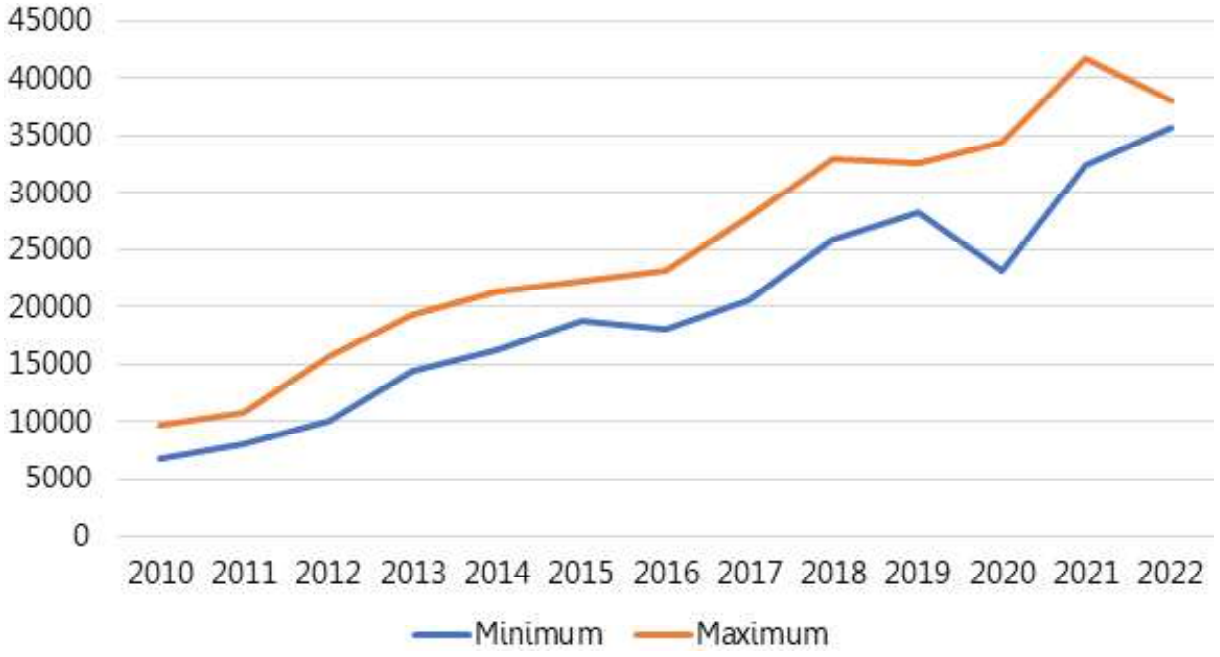
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	246	245	252	247	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	8219.714	9699.781	12631.56	16520.16	18386.71	20281.75	20602.93	24710.3	28738.58	30032.81	30045.44	36406.83	36999.92
Std. Deviation	883.413	641.026	1668.199	1172.774	1204.195	661.192	1259.115	1685.533	1680.371	886.127	1980.185	2377.892	732.985
Coefficient of Variation	0.107	0.066	0.132	0.071	0.065	0.033	0.061	0.068	0.058	0.03	0.066	0.065	0.02
Skewness	0.073	-0.668	0.214	-0.086	0.379	0.498	0.017	-0.569	0.334	0.476	-0.666	0.49	-0.082
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-1.558	-0.466	-1.145	-0.904	-0.782	0.643	-1.093	-0.613	-0.503	0.098	1.414	-0.833	-1.298
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.892	0.939	0.942	0.94	0.959	0.979	0.963	0.929	0.971	0.975	0.941	0.942	0.934
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	0.029
Minimum	6885.7	8157.4	10103	14516	16336	18828	18094	20710	25891.8	28257.1	23184.05	32443.15	35661.25
Maximum	9674.3	10762	15795	19407	21375	22295	23186	27918	32911.55	32535.9	34411.65	41619.95	38087.25

Source: From researcher's data analysis



Graph 13 : Mean Values of the Index

Source: From researcher's data analysis

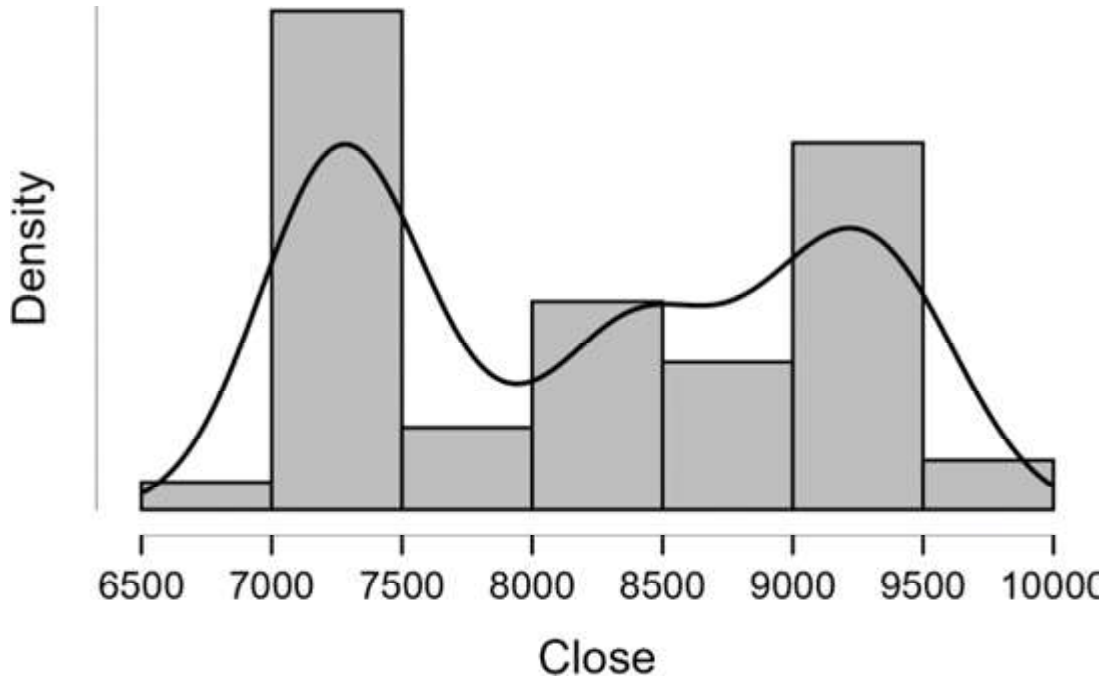


Graph 14 : Maximum and Minimum values of the index

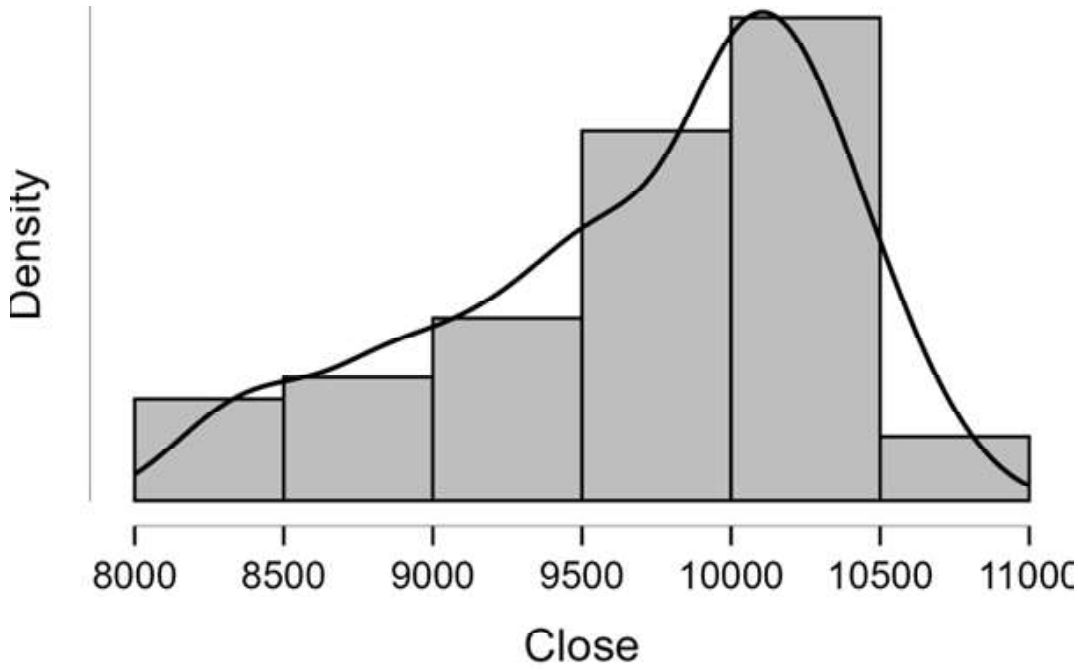
Source: From researcher's data analysis

Distribution Plots

2010



2011



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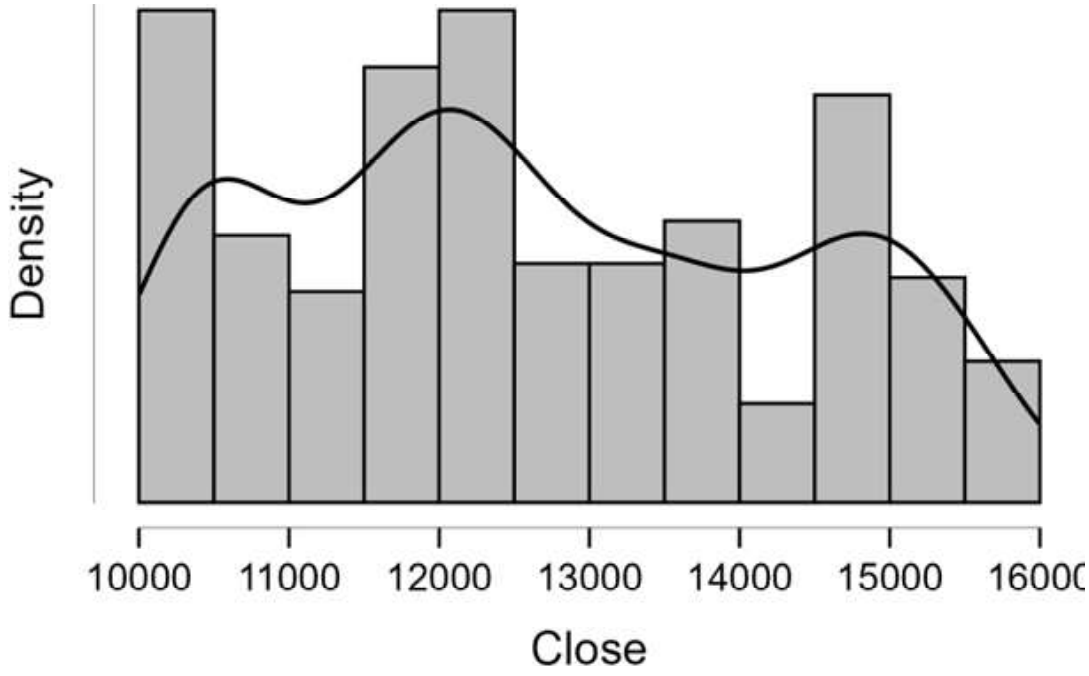
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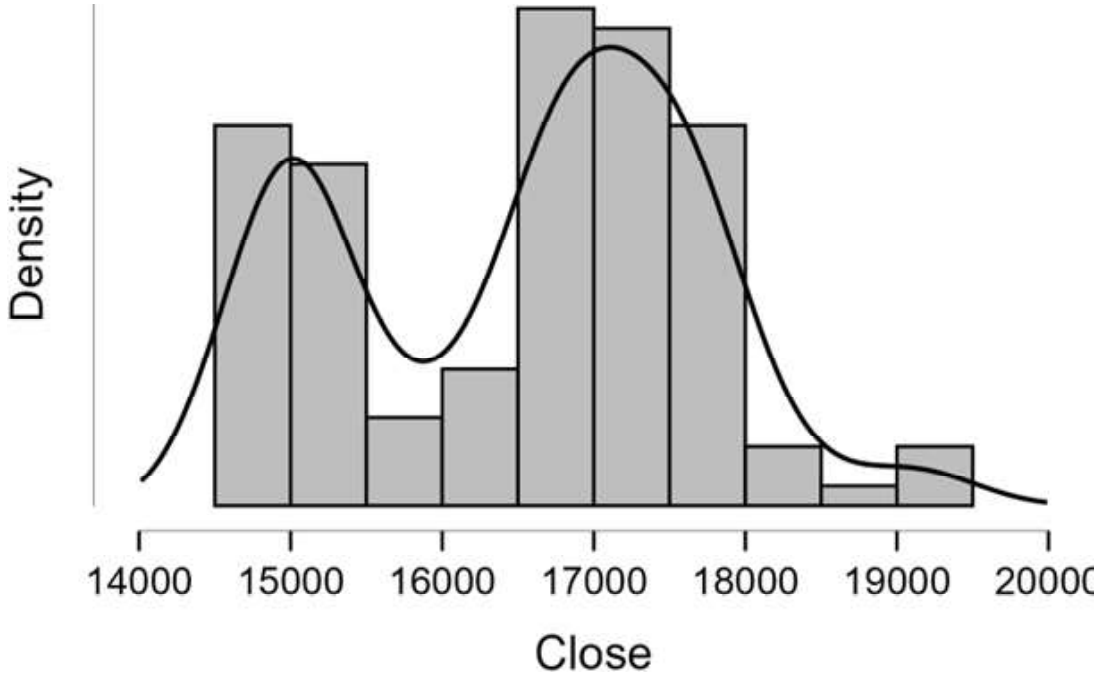
2013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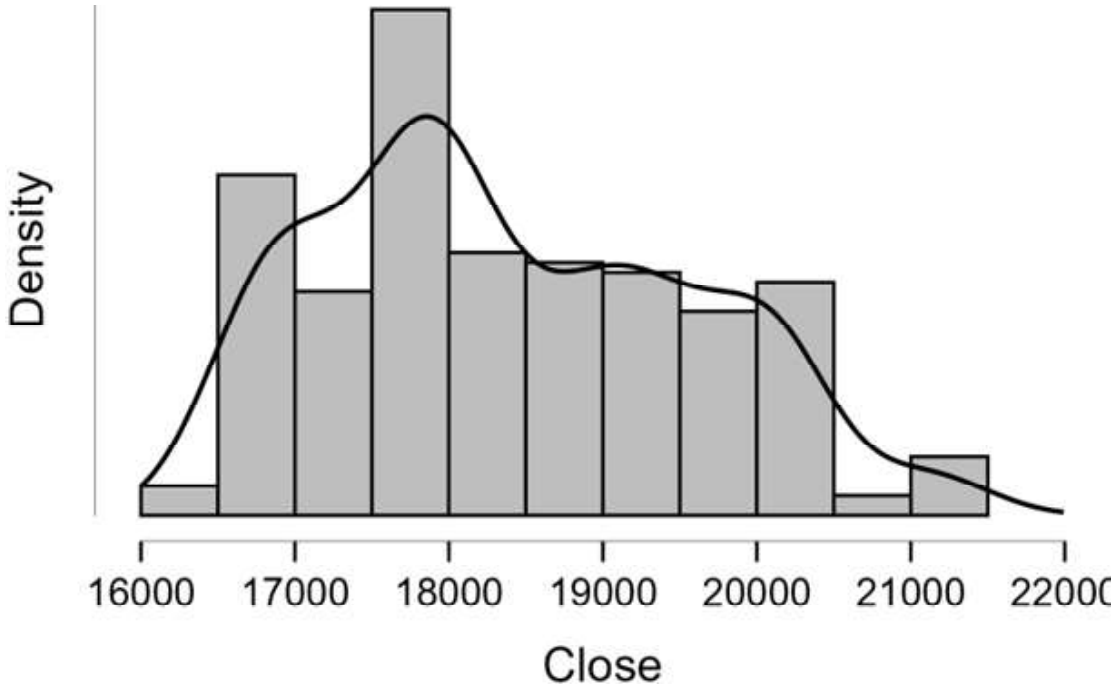
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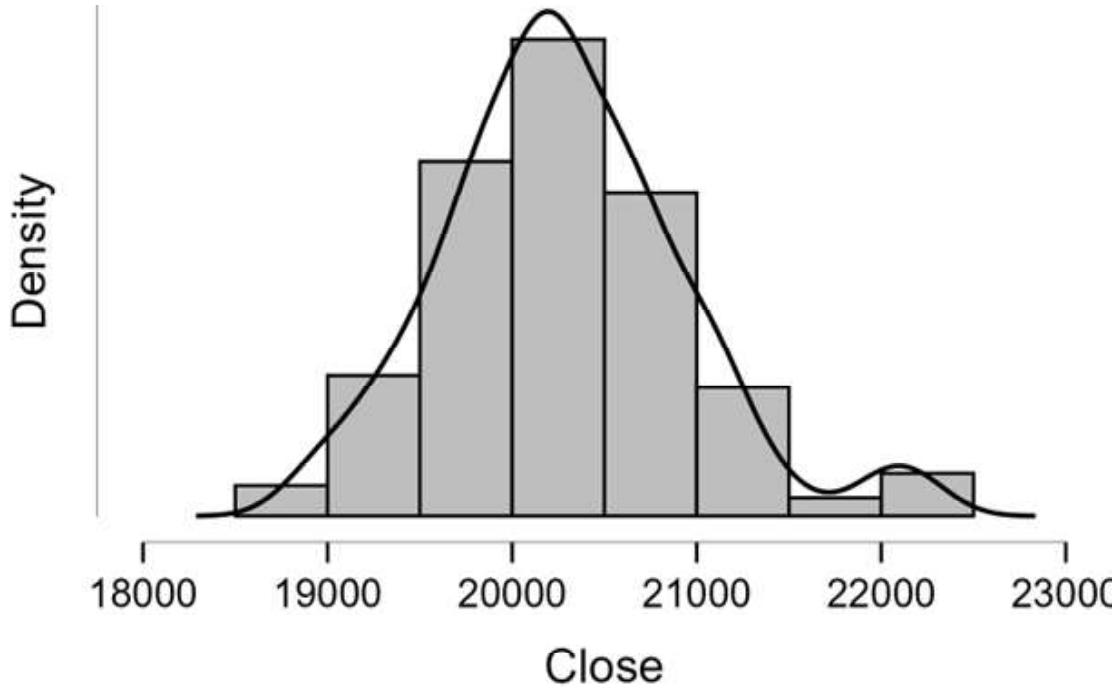
2015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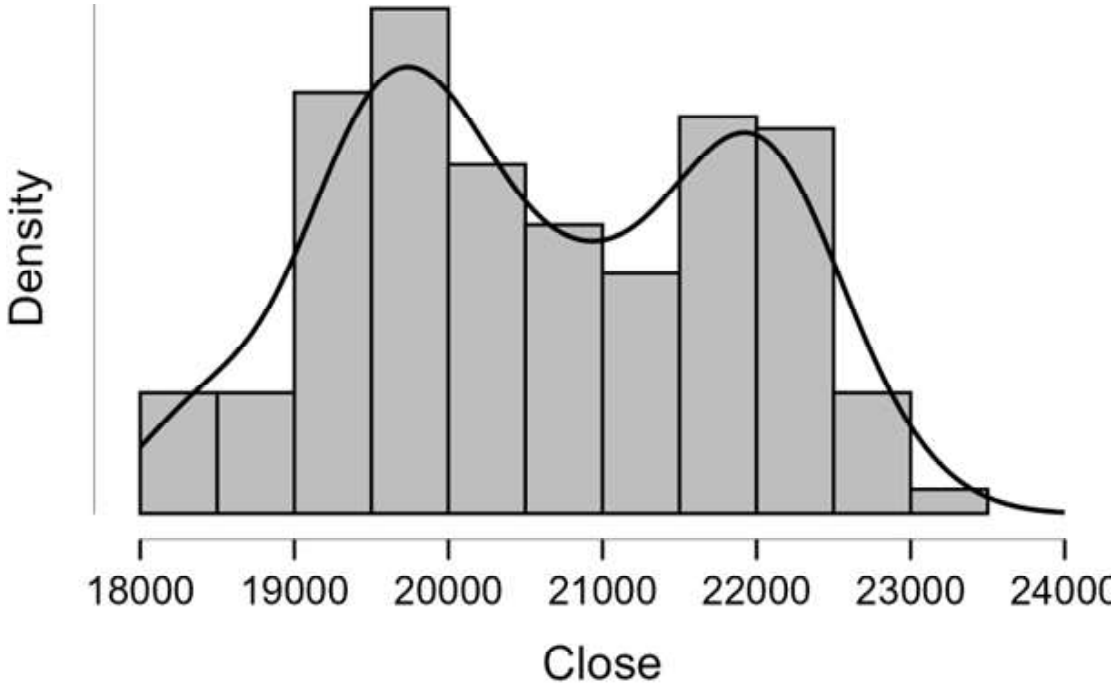
2016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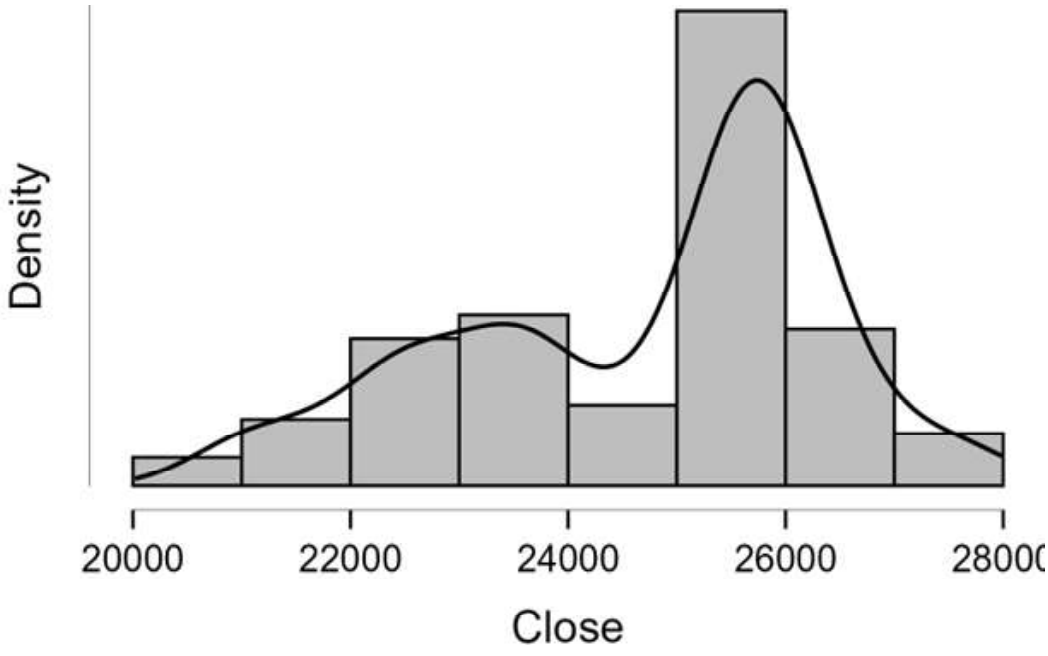
2017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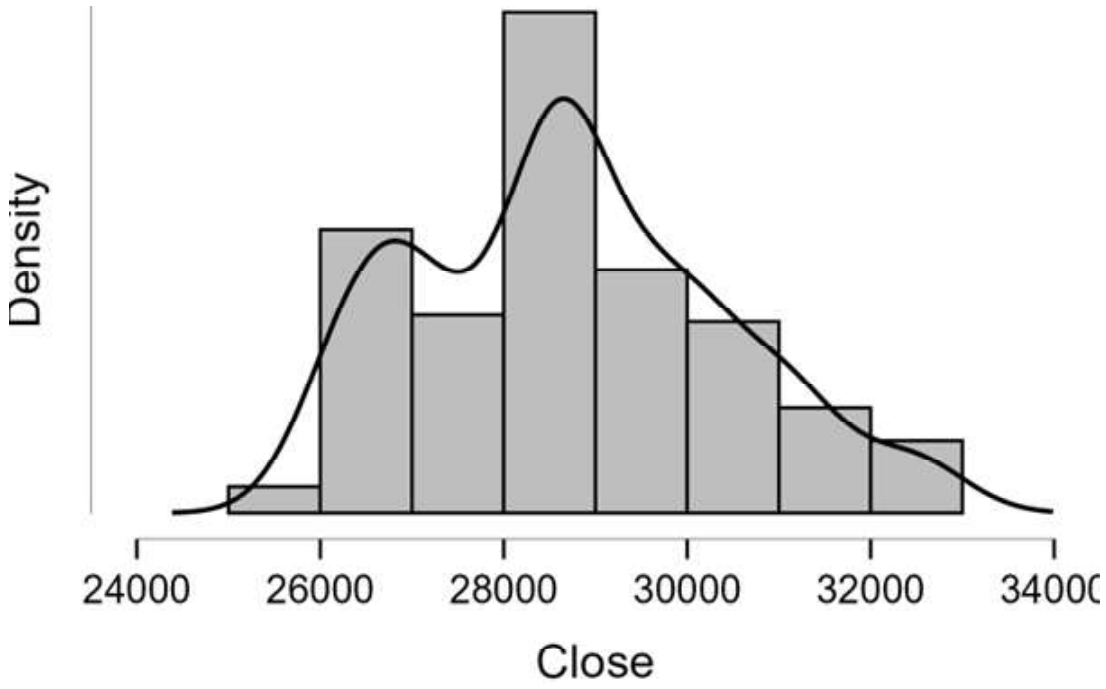
2018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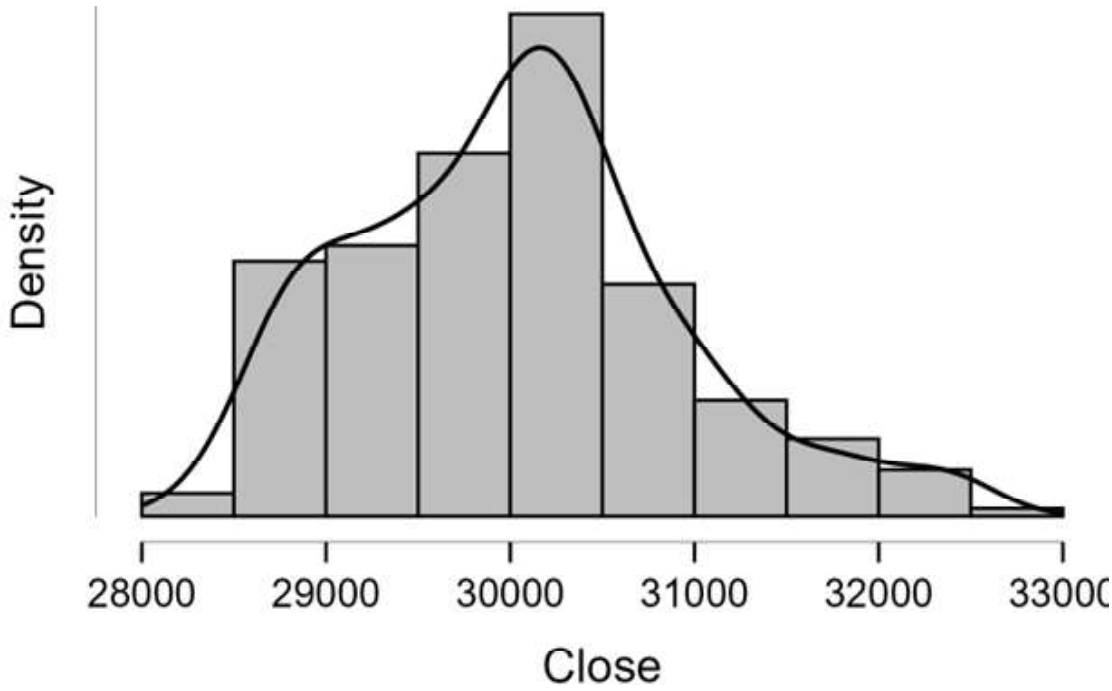
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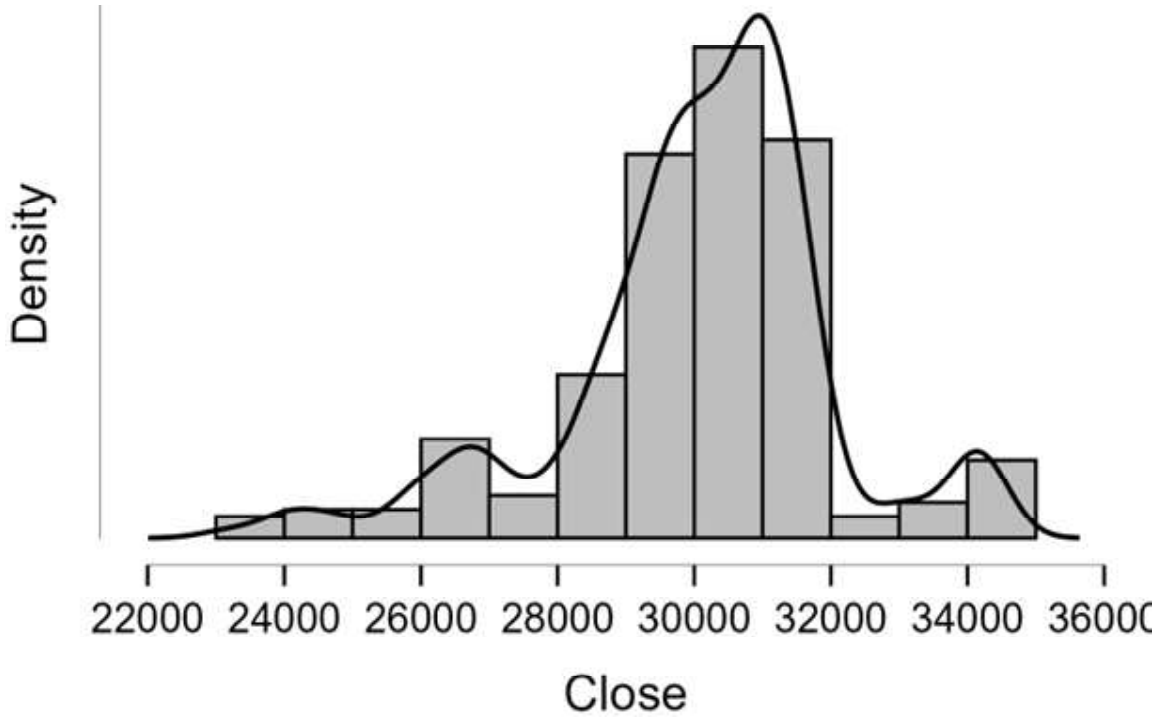
2020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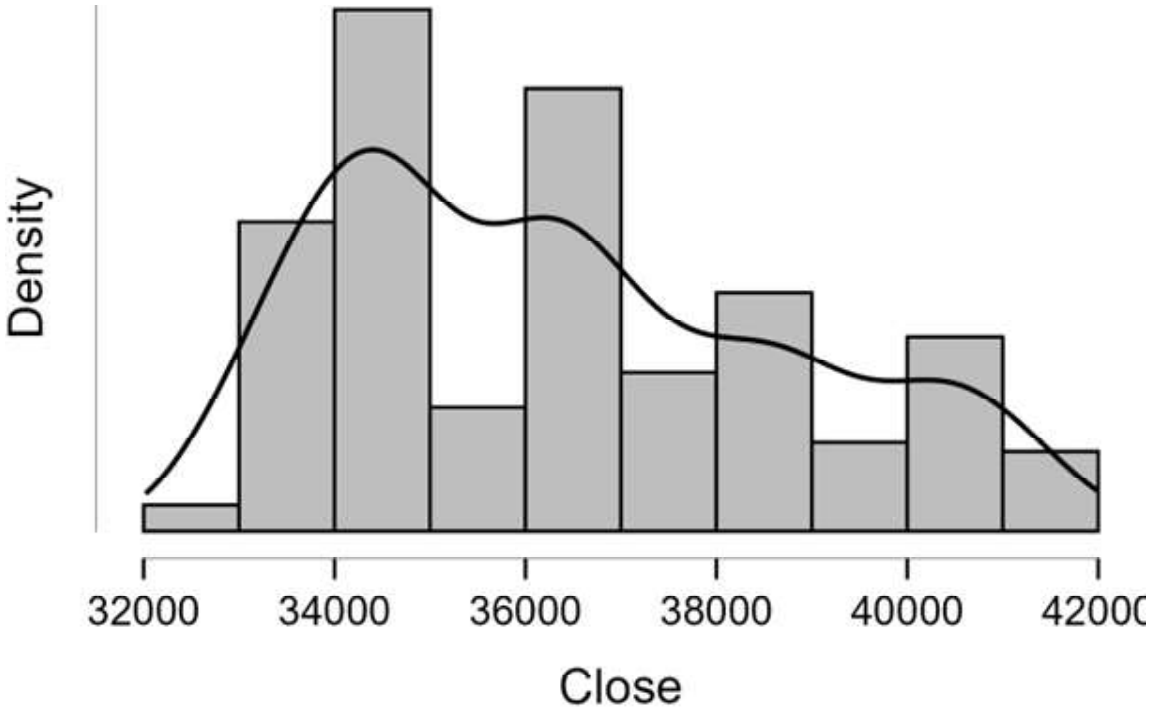
2021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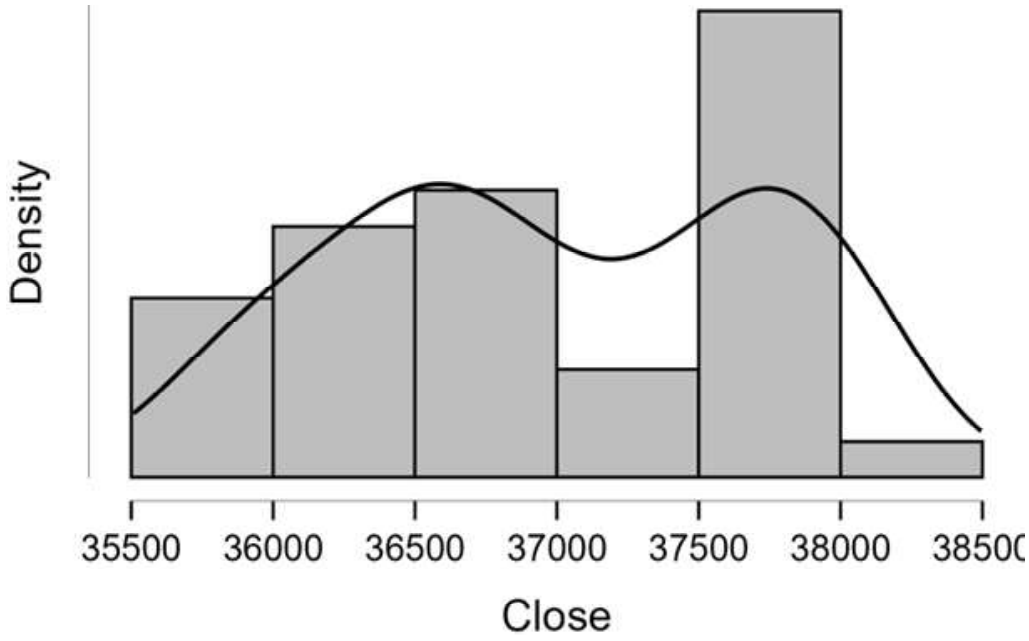
2022



Source: From researcher's data analysis

Table 27 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.5570	1.7955	Weibull	-0.3108	3.2174	Weibull
2011	-0.5674	1.7625	Weibull	0.0358	27.9615	Fréchet
2012	-0.2367	4.2250	Weibull	-0.5797	1.7251	Weibull
2013	-0.2593	3.8561	Weibull	-0.3880	2.5775	Weibull
2014	-0.0932	10.7273	Weibull	-0.5554	1.8005	Weibull
2015	-0.1513	6.6079	Weibull	-0.5171	1.9338	Weibull
2016	-0.2959	3.3797	Weibull	-0.3519	2.8419	Weibull
2017	-0.4896	2.0427	Weibull	-0.0464	21.5436	Weibull
2018	-0.1680	5.9510	Weibull	-0.5150	1.9418	Weibull
2019	-0.1317	7.5951	Weibull	-0.5538	1.8058	Weibull
2020	-0.3638	2.7486	Weibull	-0.1468	6.8101	Weibull
2021	-0.0082	122.5913	Weibull	-0.5160	1.9380	Weibull
2022	-0.6772	1.4768	Weibull	-0.3517	2.8434	Weibull

Source: From researcher's data analysis

Table 28 : Tail index and classification of the Index

	Shape	Scale	Comments based on the Index values
2010	5.751763	6885.7	heavy-tailed and moments of higher order exists
2011	5.759591	8157.4	heavy-tailed and moments of higher order exists
2012	4.587611	10103	heavy-tailed and moments of higher order exists
2013	7.765967	14516	heavy-tailed and moments of higher order exists
2014	8.478468	16336	heavy-tailed and moments of higher order exists
2015	13.33169	18828	heavy-tailed and moments of higher order exists
2016	7.69643	18094	heavy-tailed and moments of higher order exists
2017	5.652276	20710	heavy-tailed and moments of higher order exists
2018	9.598601	25891.8	heavy-tailed and moments of higher order exists
2019	16.27714	28257.1	heavy-tailed and moments of higher order exists
2020	3.834201	23184.05	heavy-tailed and moments of higher order exists
2021	8.70419	32443.15	heavy-tailed and moments of higher order exists
2022	25.26762	35661.25	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 29 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	696.8023	8221.2132	Normal
2011	1.973826	-1	447.979897	9704.768682	Stable
2012	2.0000	0.0000	1275.9890	12640.6190	Normal
2013	2	0	884.9768	16516.4448	Normal
2014	2	0	894.3109	18398.3861	Normal
2015	1.8821	0.9338	432.8314	20217.3900	Stable
2016	2	0	964.6247	20603.7305	Normal
2017	2	0	1207.065	24682.631	Normal
2018	2	0	1222.573	28752.769	Normal
2019	1.964616	1	611.37504	30010.68981	Stable
2020	1.137353	-0.5132	839.479149	30452.13612	Stable
2021	2	0	1749.366	36438.381	Normal
2022	2	0	562.3036	36998.6641	Normal

Source: From researcher's data analysis

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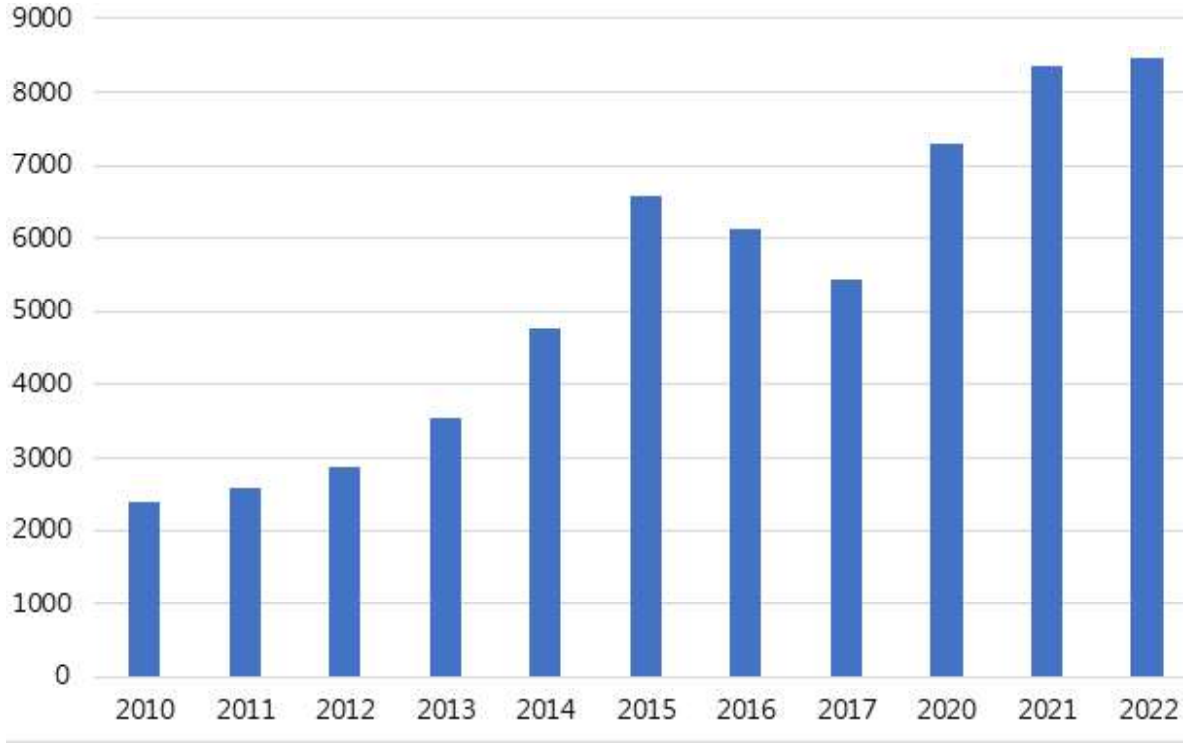
Table 30 : Descriptive Statistics and Test for Normal Probability Model

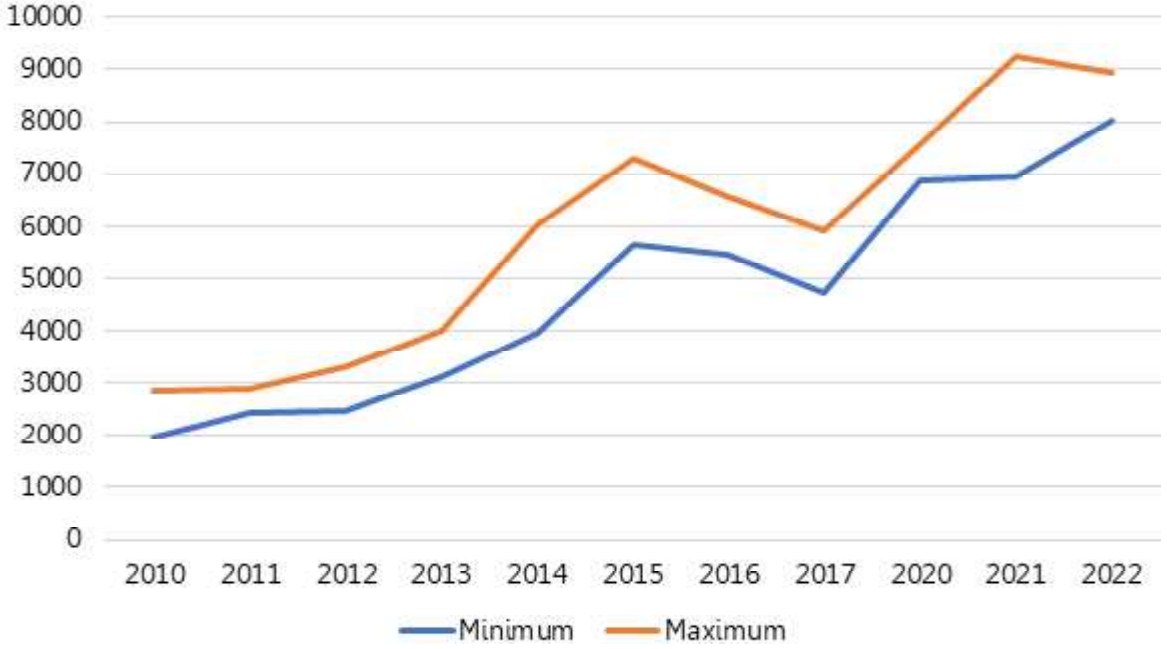
	2010	2011	2012	2013	2014	2015	2016	2017	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	30	248	37
Missing	0	0	0	0	0	0	0	0	0	0	0
Mean	2393.199	2595.728	2866.832	3540.369	4767.641	6588.349	6120.844	5429.454	7282.392	8346.801	8465.923
Std. Deviation	246.335	98.178	210.316	241.532	698.734	370.269	209.101	303.83	221.53	645.169	259.936
Coefficient of Variation	0.103	0.038	0.073	0.068	0.147	0.056	0.034	0.056	0.03	0.077	0.031
Skewness	0.428	0.698	0.328	-0.05	0.445	-0.146	-0.412	-0.148	-0.524	-0.617	0.123
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.427	0.155	0.388
Kurtosis	-0.861	-0.25	-1.029	-1.235	-1.426	-0.522	-0.162	-1.022	-0.931	-1.006	-1.143
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.833	0.308	0.759
Shapiro-Wilk	0.926	0.94	0.949	0.946	0.848	0.986	0.977	0.955	0.916	0.894	0.951
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	0.013	< .001	< .001	0.021	< .001	0.102
Minimum	1970.7	2437.6	2475	3116.5	3968.5	5658.3	5441.3	4730.3	6882.16	6956.38	8005.25
Maximum	2855.1	2886.7	3315.6	3986.9	6013.6	7312.4	6561.4	5923.4	7580.96	9229.6	8928.85

Source: From researcher's data analysis



Graph 15 : Mean values of the index

Source: From researcher's data analysis

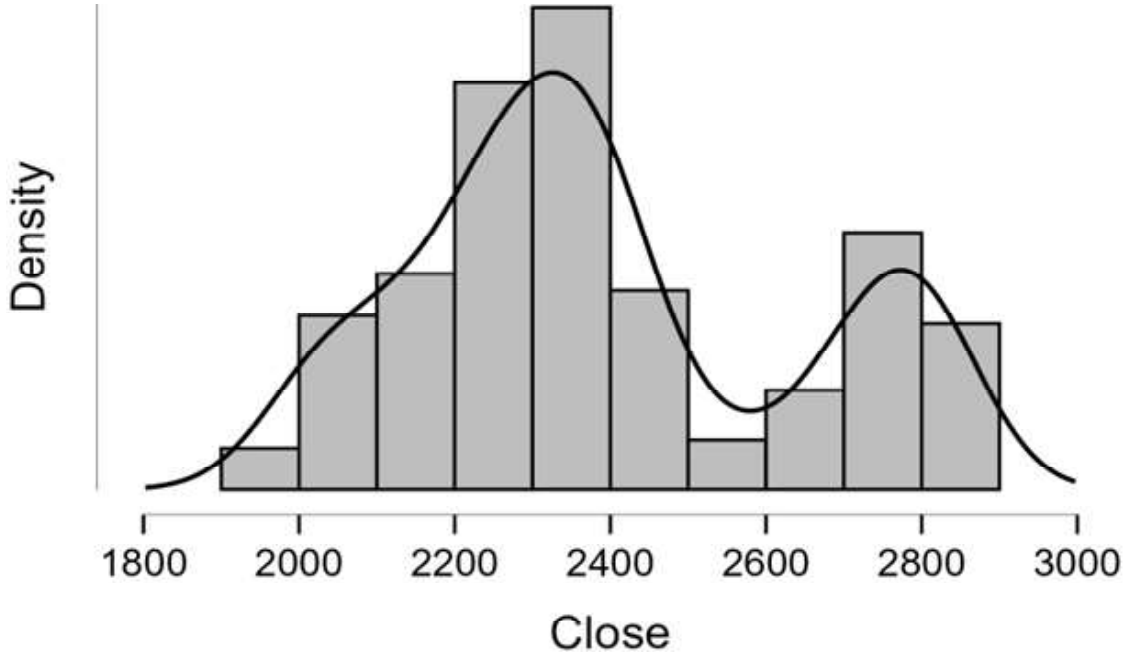


Graph 16 : Maximum and Minimum values of the Index

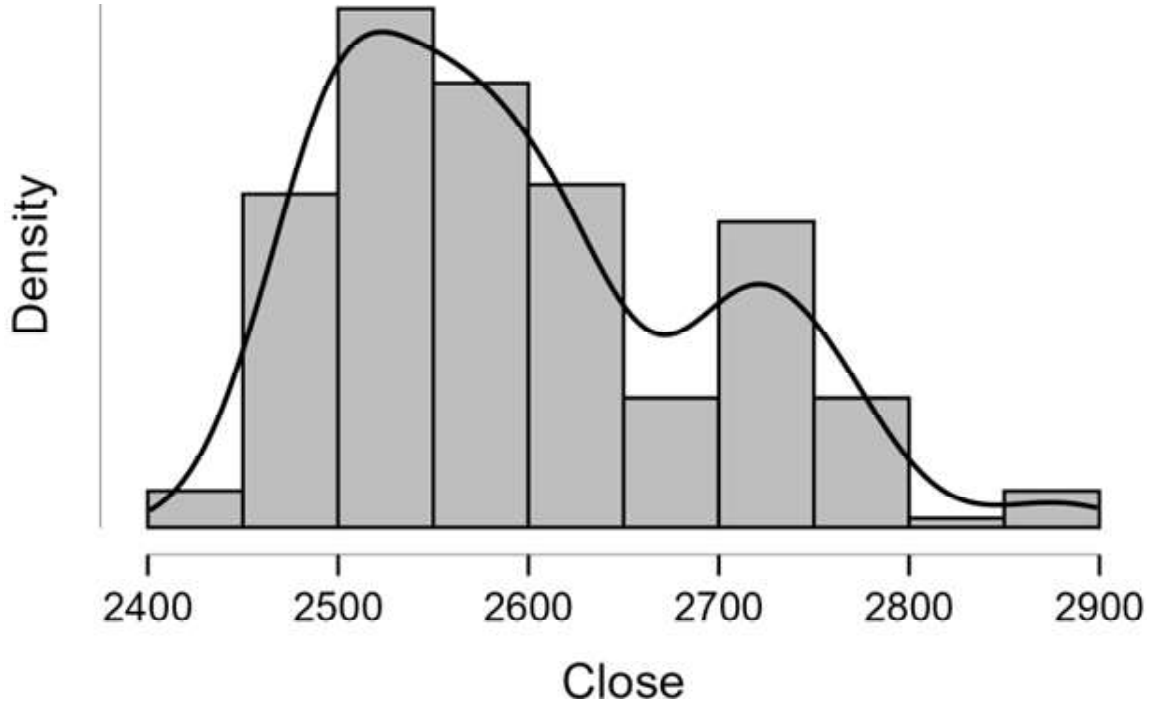
Source: From researcher's data analysis

Distribution Plots

2010



2011



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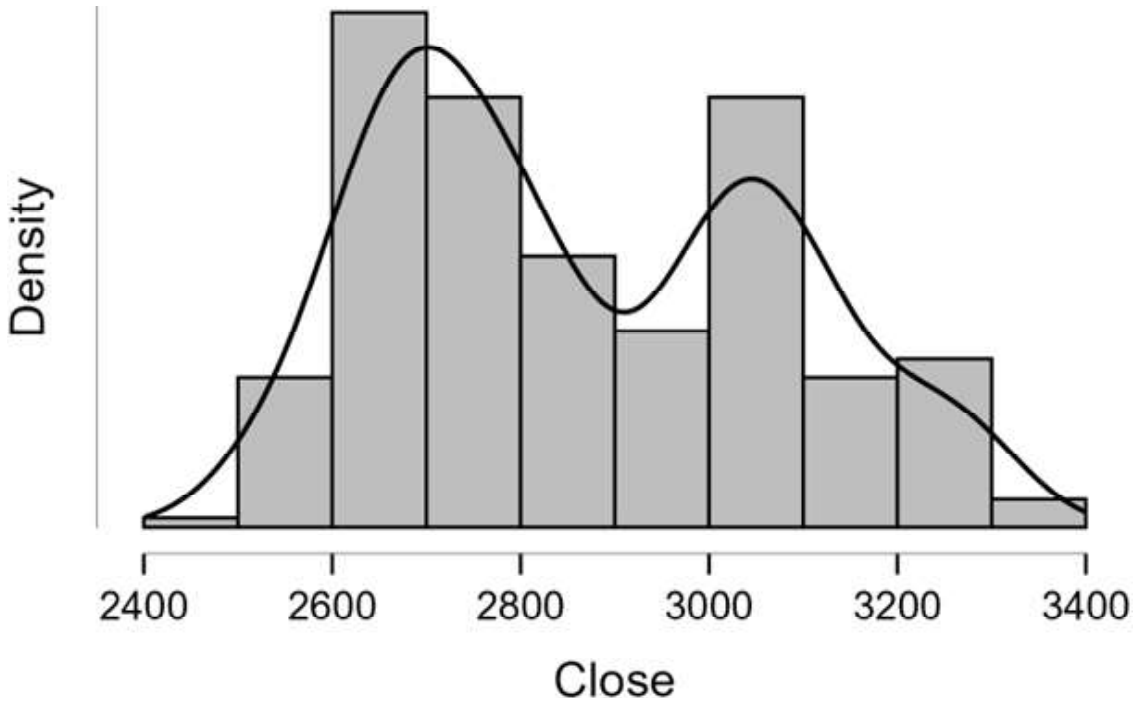
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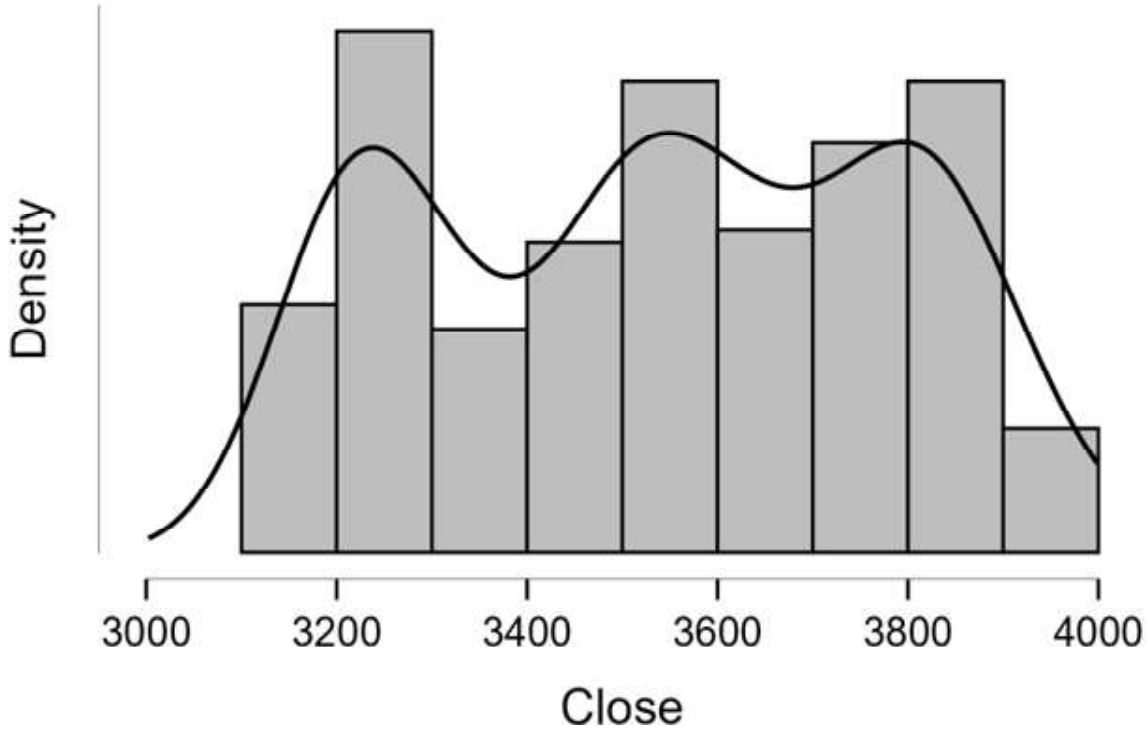
2013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3400
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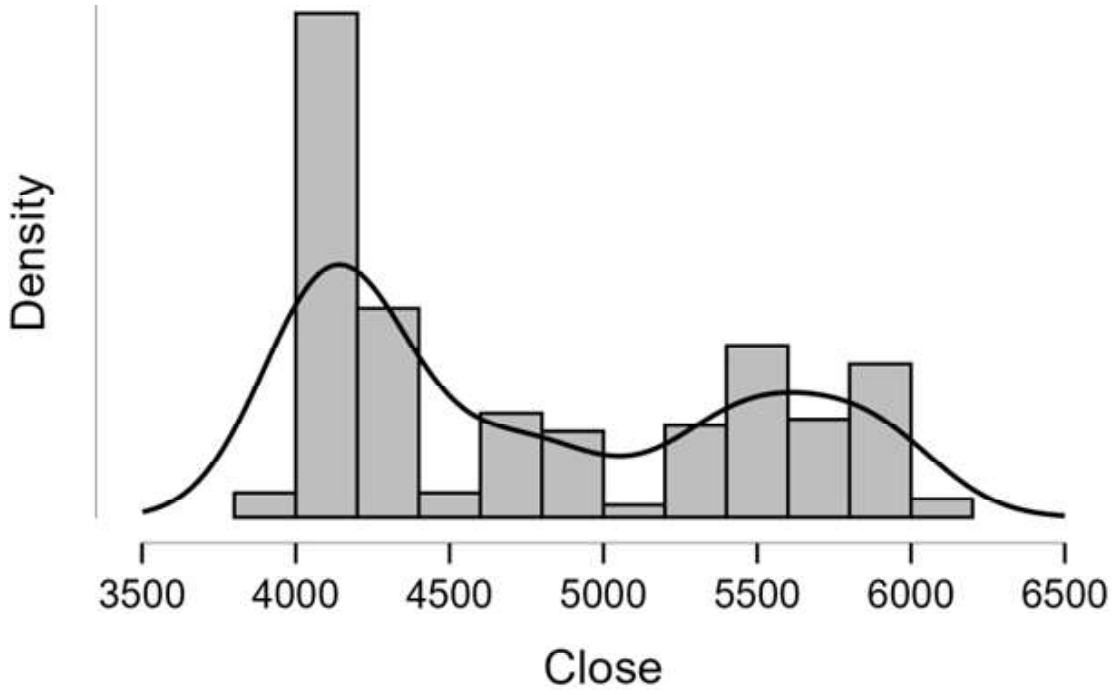
Close

2014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6500
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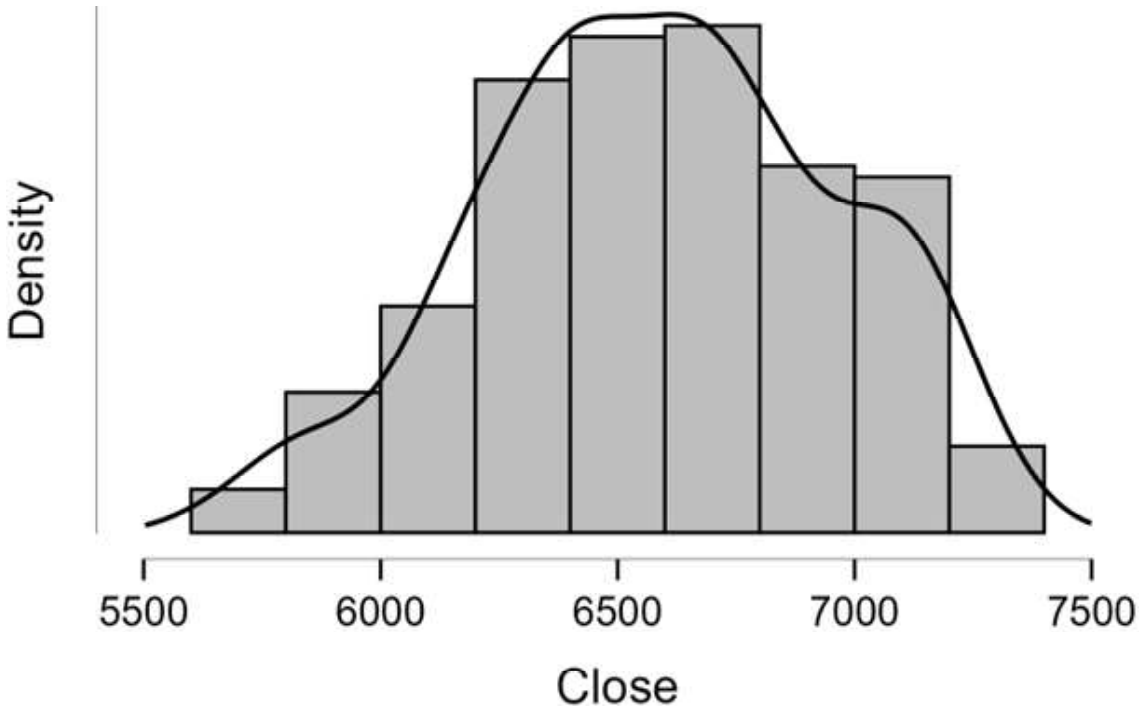
2015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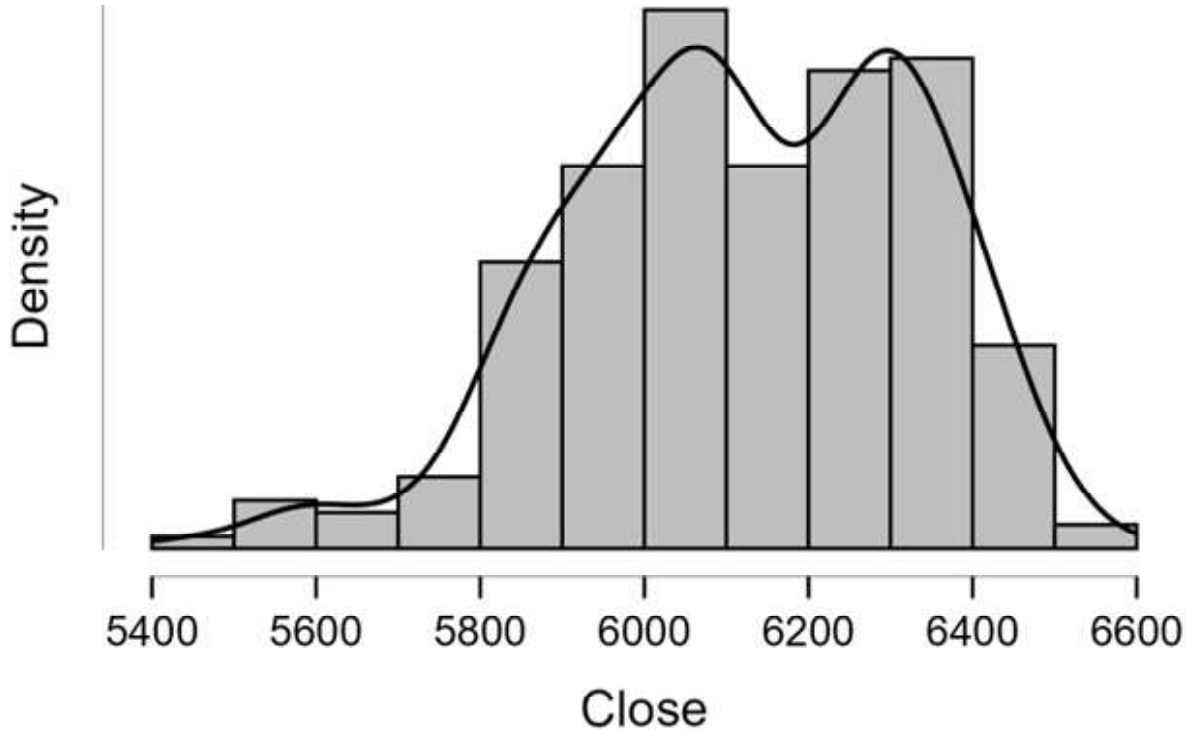
2016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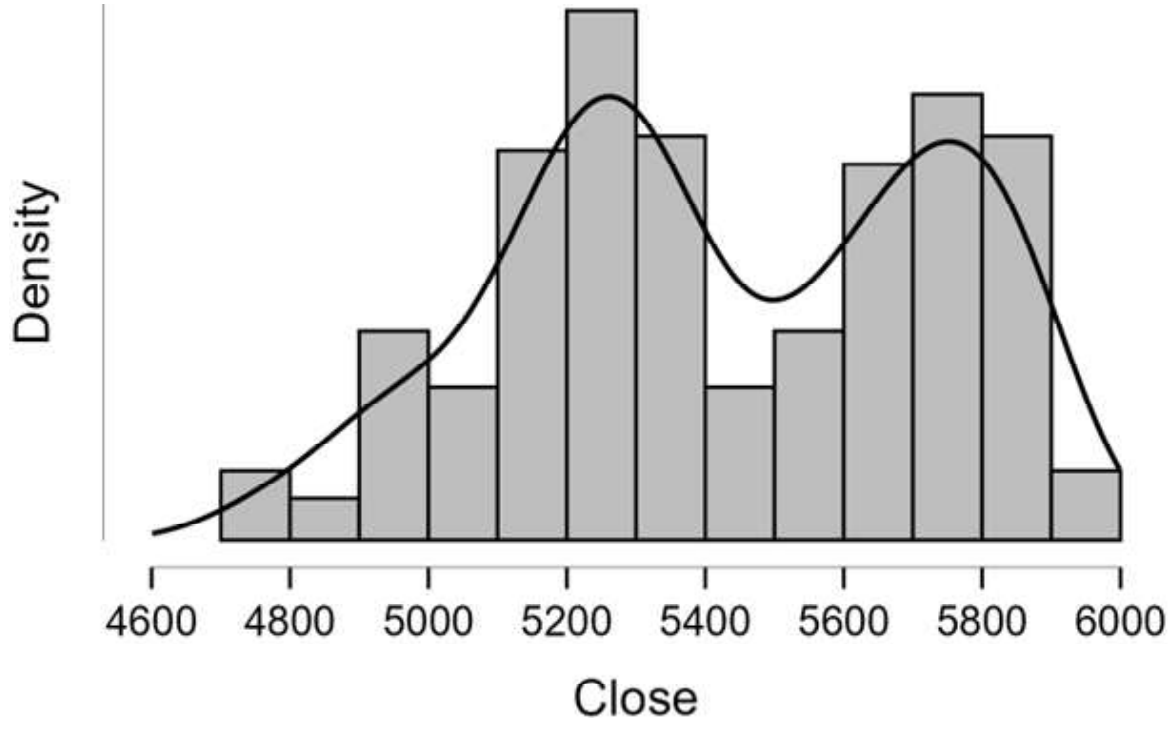
6400
6600
Close

2017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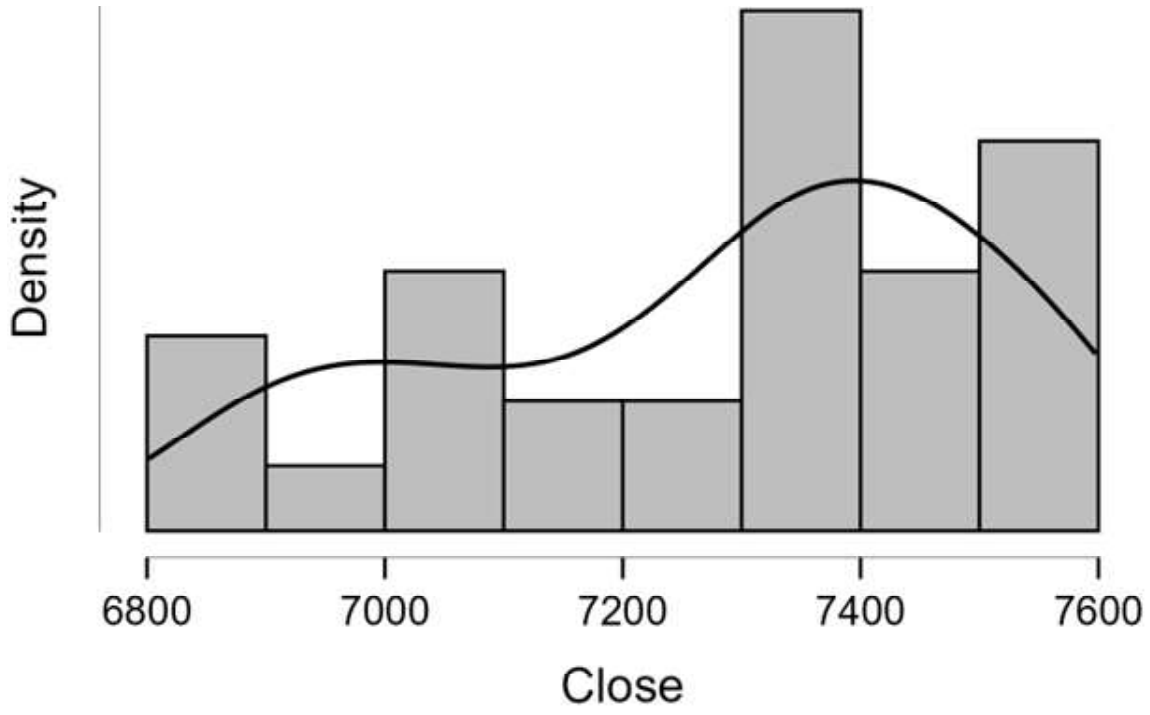
5800
6000
Close

2020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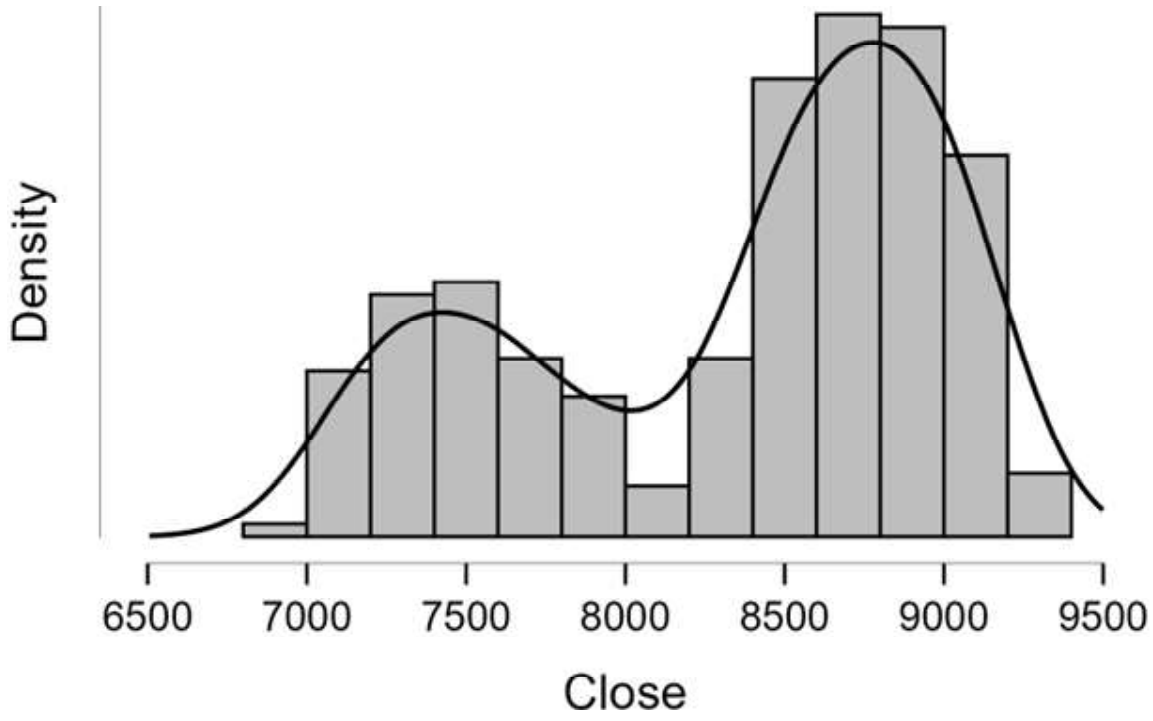
2021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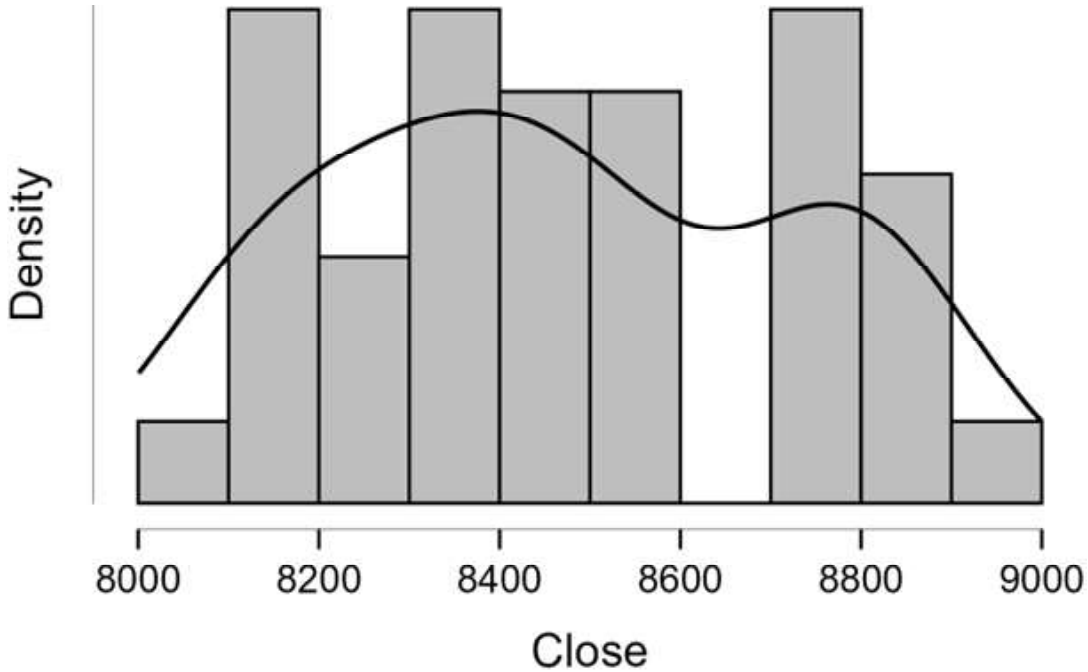
8500
9000
9500
Close



Source: From researcher's data analysis

Table 31 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.1031	9.7014	Weibull	-0.5324	1.8782	Weibull
2011	0.0565	17.7145	Fréchet	-0.5912	1.6914	Weibull
2012	-0.1267	7.8920	Weibull	-0.4469	2.2378	Weibull
2013	-0.4358	2.2948	Weibull	-0.4447	2.2488	Weibull
2014	0.9002	1.1109	Fréchet	-0.7378	1.3554	Weibull
2015	-0.3959	2.5260	Weibull	-0.2406	4.1557	Weibull
2016	-0.4130	2.4216	Weibull	-0.1369	7.3021	Weibull
2017	-0.5717	1.7491	Weibull	-0.2506	3.9905	Weibull
2018						
2019						
2020	-0.7795	1.2829	Weibull	0.0388	25.7819	Fréchet
2021	-0.7418	1.3480	Weibull	0.2282	4.3813	Fréchet
2022	-0.3386	2.9537	Weibull	-0.4470	2.2370	Weibull

Source: From researcher's data analysis

Table 32 : Tail index and classification of the Index

	Shape	Scale	Comments based on the Index values
2010	5.211273	1970.7	heavy-tailed and moments of higher order exists
2011	15.84176	2437.6	heavy-tailed and moments of higher order exists
2012	6.824789	2475	heavy-tailed and moments of higher order exists
2013	7.869724	3116.5	heavy-tailed and moments of higher order exists
2014	5.690951	3968.5	heavy-tailed and moments of higher order exists
2015	6.538675	5658.3	heavy-tailed and moments of higher order exists
2016	8.412032	5441.3	heavy-tailed and moments of higher order exists
2017	7.228428	4730.3	heavy-tailed and moments of higher order exists
2018	-	-	heavy-tailed and moments of higher order exists
2019	-	-	heavy-tailed and moments of higher order exists
2020	16.27451	6882.16	heavy-tailed and moments of higher order exists
2021	5.499409	6956.38	heavy-tailed and moments of higher order exists
2022	16.69215	8005.25	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 33 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	180.7788	2396.2067	Normal
2011	1.98254	0	68.74279	2597.702574	Stable
2012	2.0000	0.0000	159.2326	2868.5889	Normal
2013	2	0	186.4982	3540.0432	Normal
2014	2	0	538.1004	4775.6034	Normal
2015	2.0000	0.0000	271.2826	6587.1287	Normal
2016	2	0	150.3488	6118.8376	Normal
2017	2	0	231.665	5428.464	Normal
2018					Stable
2019					Stable
2020	2	0	161.316	7279.379	Normal
2021	2	0	471.2221	8335.4171	Normal
2022	2	0	196.974	8466.727	Normal

Source: From researcher's data analysis

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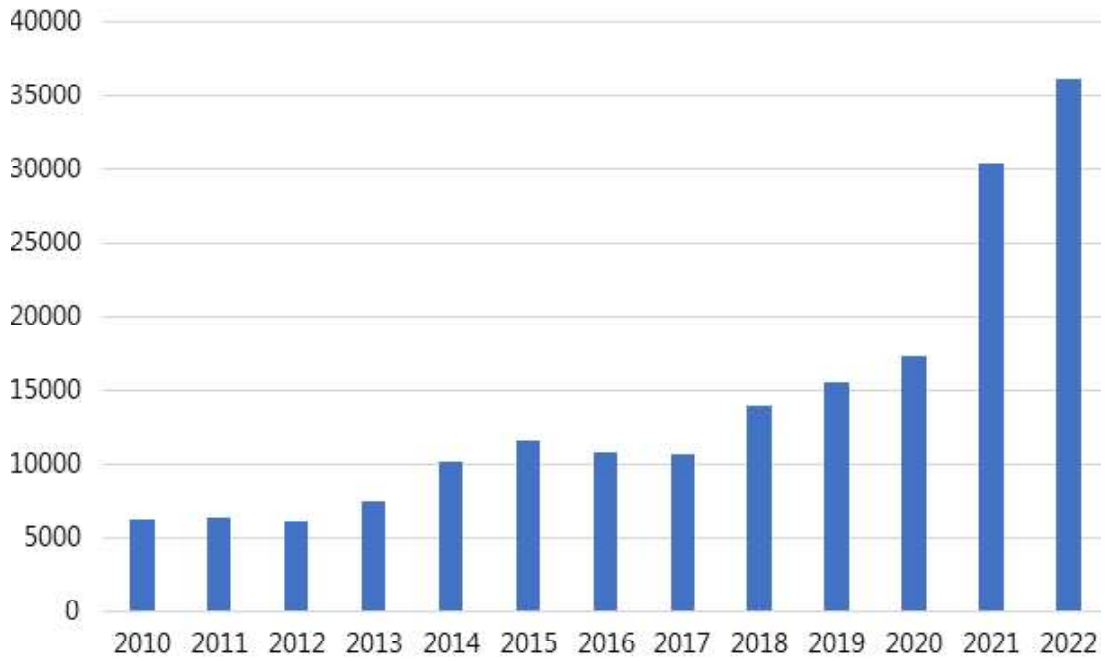
Table 34 : Descriptive Statistics and Test for Normal Probability Model

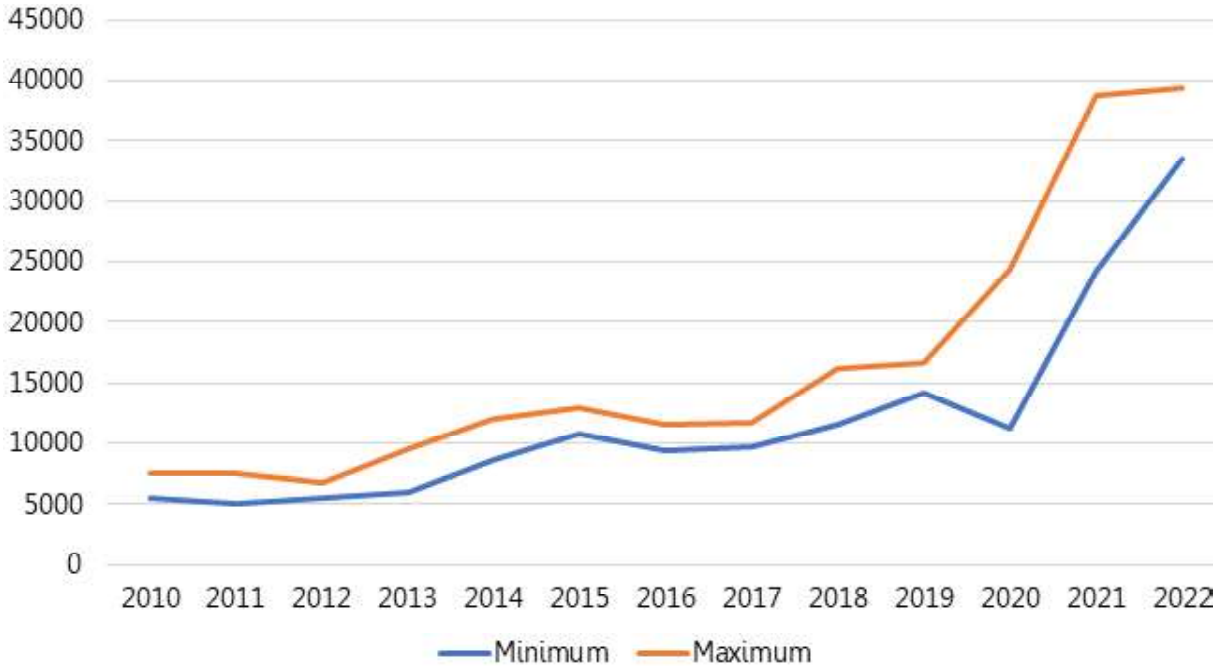
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	246	245	252	247	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	6203.24	6375.903	6124.343	7488.155	10197.66	11585.14	10724.98	10601.01	13944.19	15564.67	17281.24	30344.81	36088.04
Std. Deviation	454.679	570.729	267.078	1013.4	830.901	466.699	514.023	377.762	1116.188	475.494	3353.219	4466.006	1902.398
Coefficient of Variation	0.073	0.09	0.044	0.135	0.081	0.04	0.048	0.036	0.08	0.031	0.194	0.147	0.053
Skewness	0.811	-0.32	0.144	0.341	0.29	0.709	-0.531	0.359	0.051	-0.535	0.279	0.28	0.469
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-0.029	-0.517	-0.512	-1.237	-1.053	-0.348	-0.587	-0.268	-0.628	0.391	-0.974	-1.586	-1.456
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.924	0.975	0.982	0.924	0.955	0.94	0.952	0.981	0.977	0.977	0.958	0.859	0.859
P-value of Shapiro-Wilk	< .001	< .001	0.002	< .001	< .001	< .001	< .001	0.002	< .001	< .001	< .001	< .001	< .001
Minimum	5449.7	5087.6	5489.6	5972.7	8675.1	10798	9434.6	9750	11565.75	14146.15	11179.6	24301.45	33475.05
Maximum	7503.6	7545.9	6747.2	9579.1	11981	12855	11597	11665	16234.9	16705.4	24330.05	38701	39370.7

Source: From researcher's data analysis



Graph 17 : Mean values of the Index

Source: From researcher's data analysis

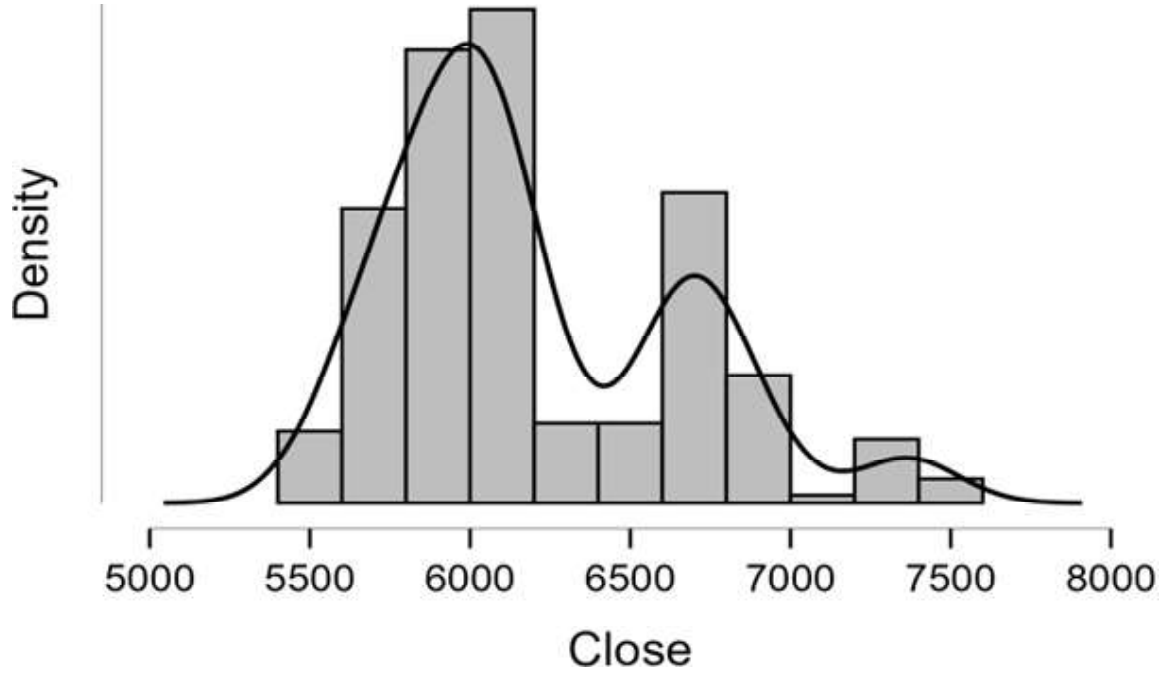


Graph 18 : Maximum and Minimum values of the Index

Source: From researcher's data analysis

Distribution Plots

2010



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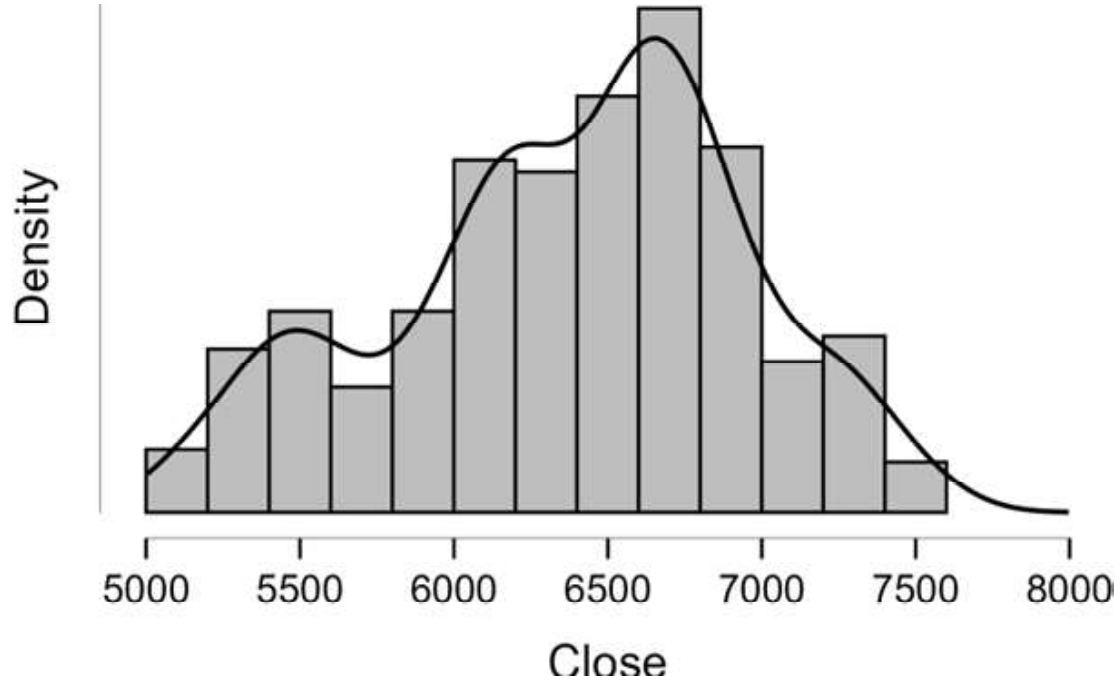
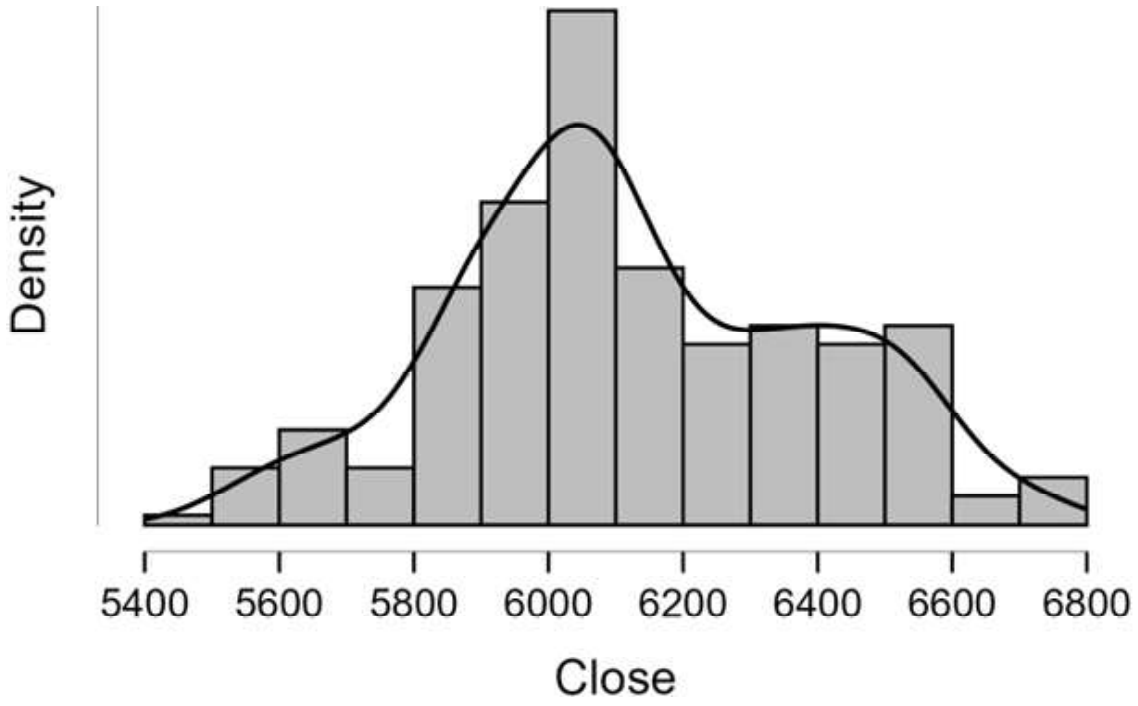


2012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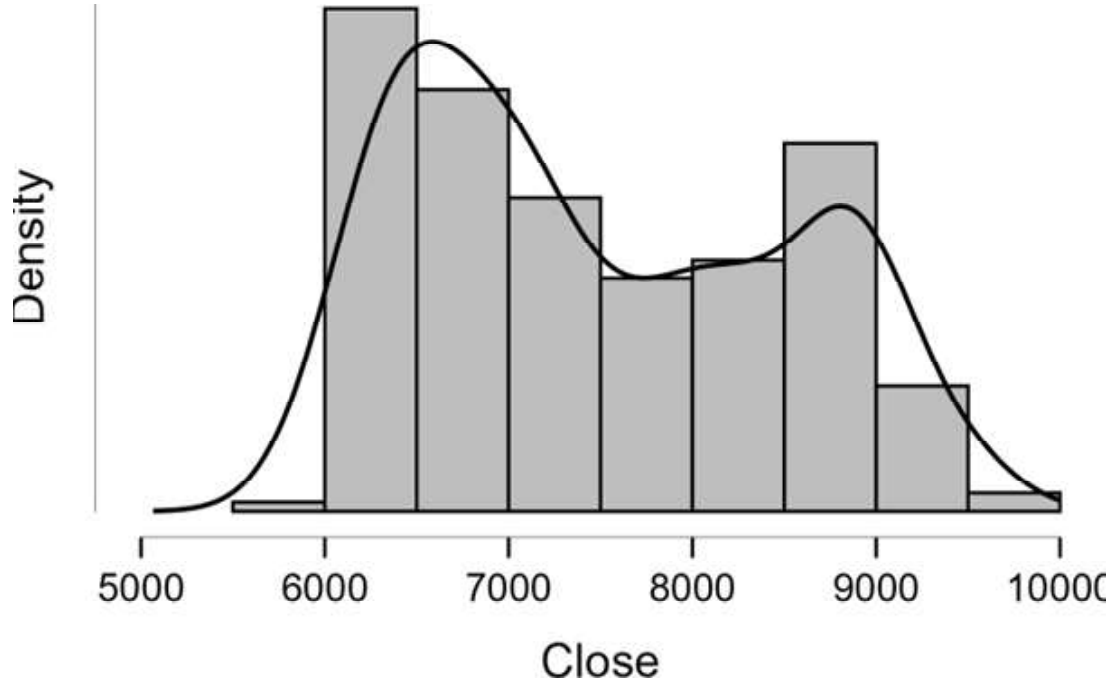
2013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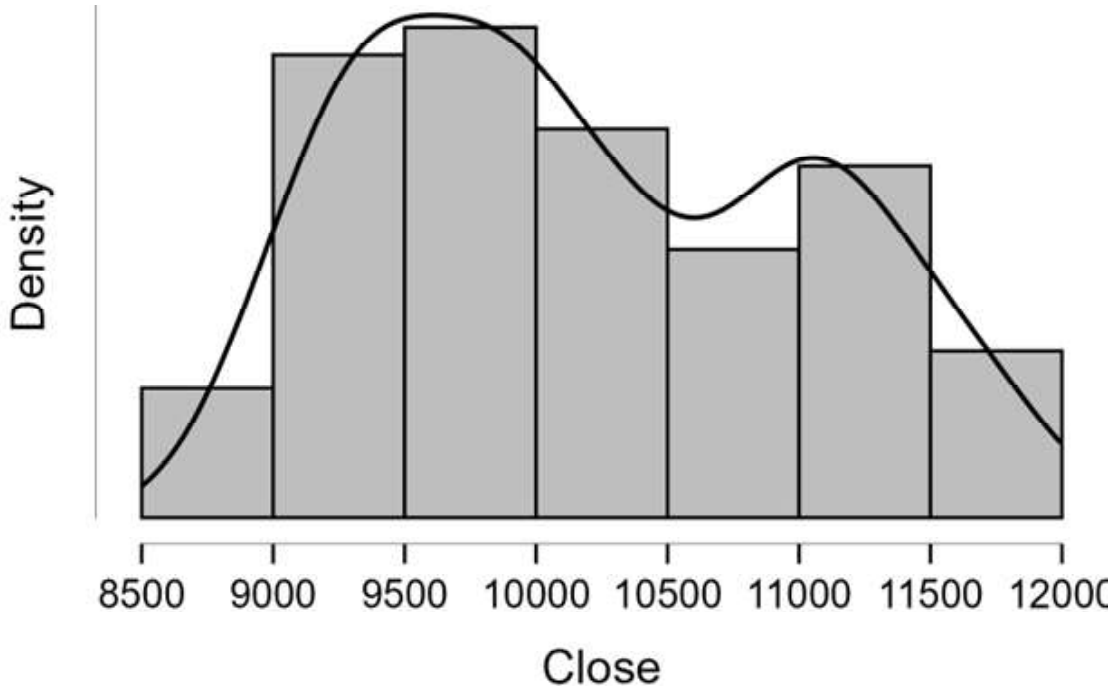
2014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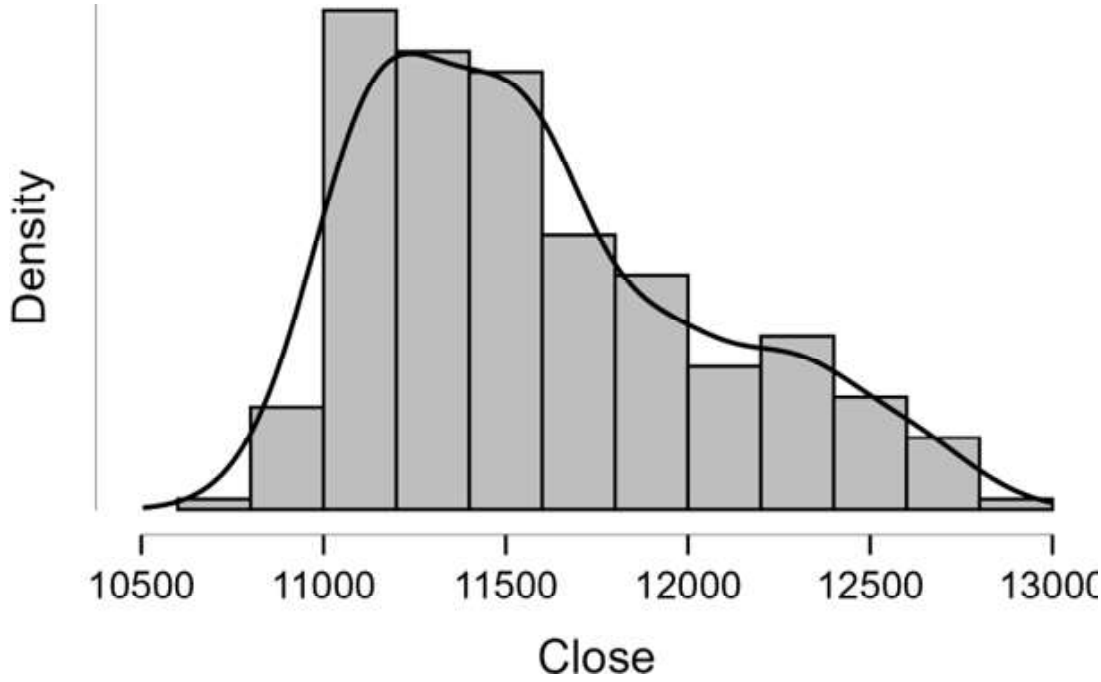
Close

2015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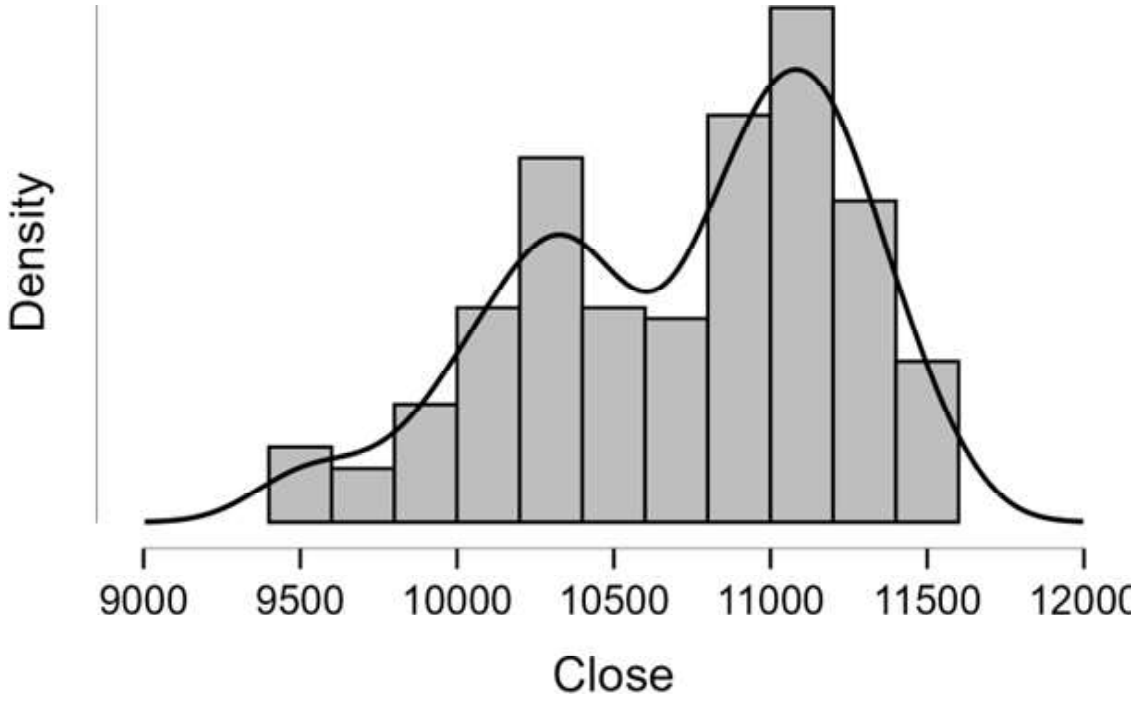
2016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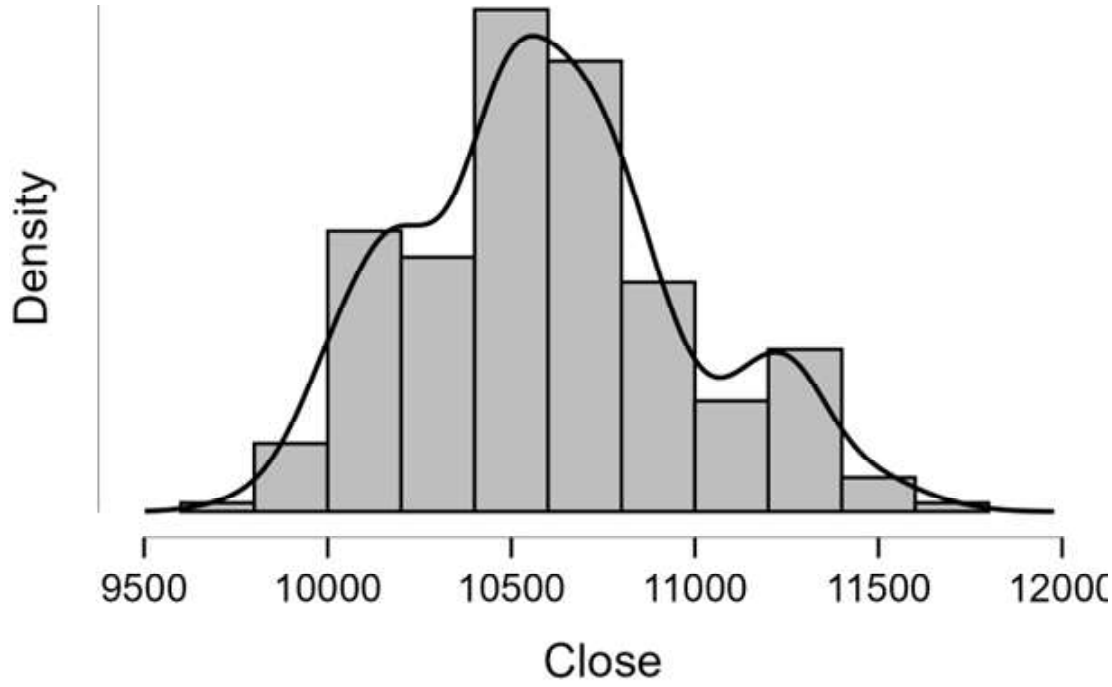
2017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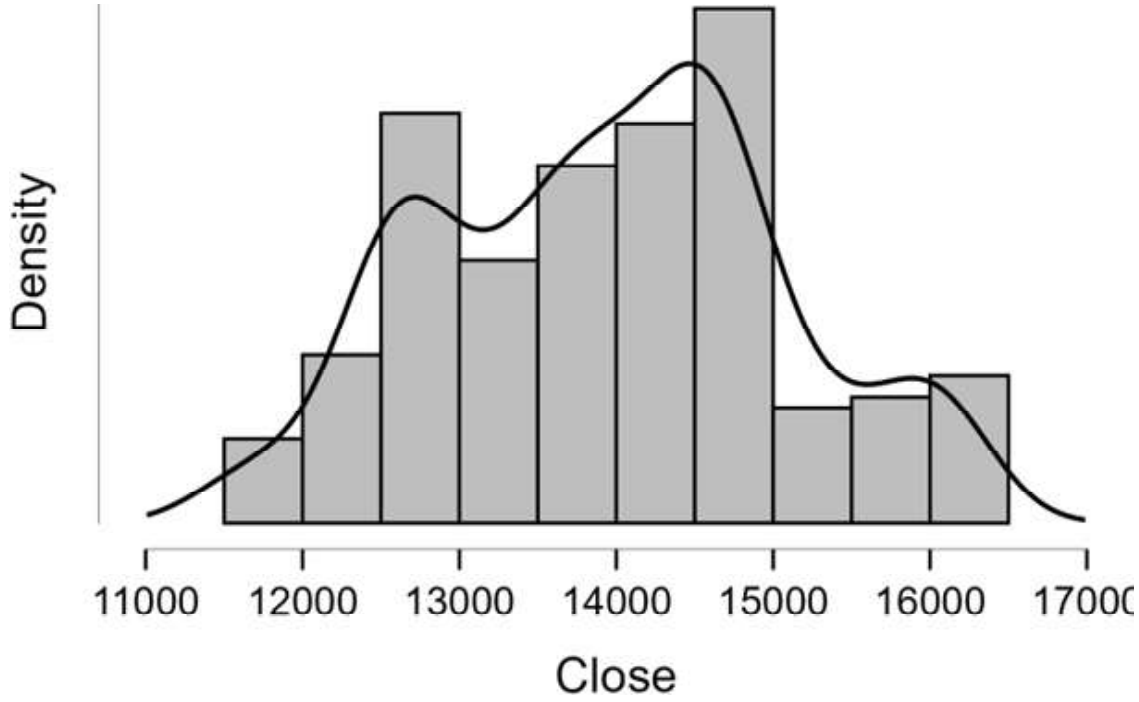
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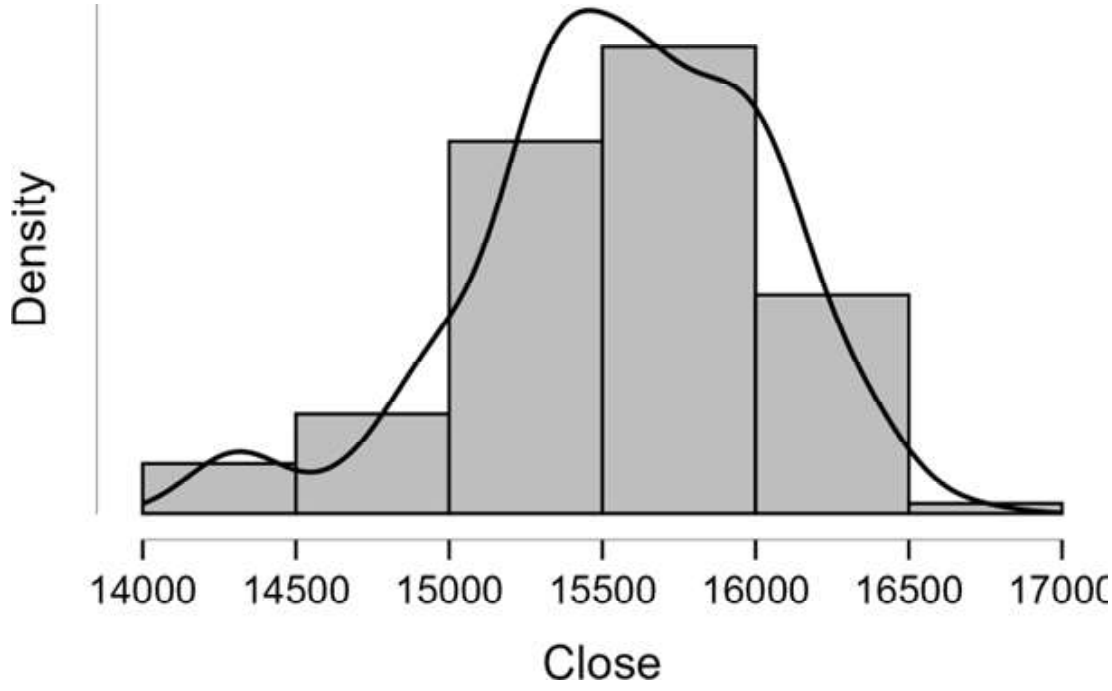
2019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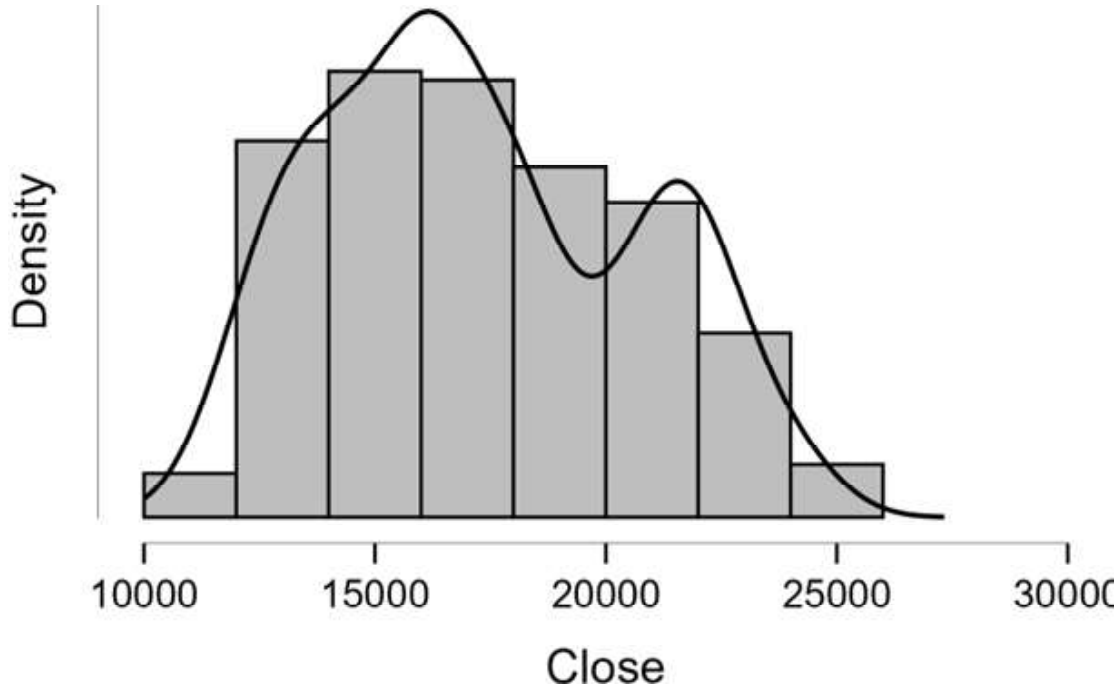
2020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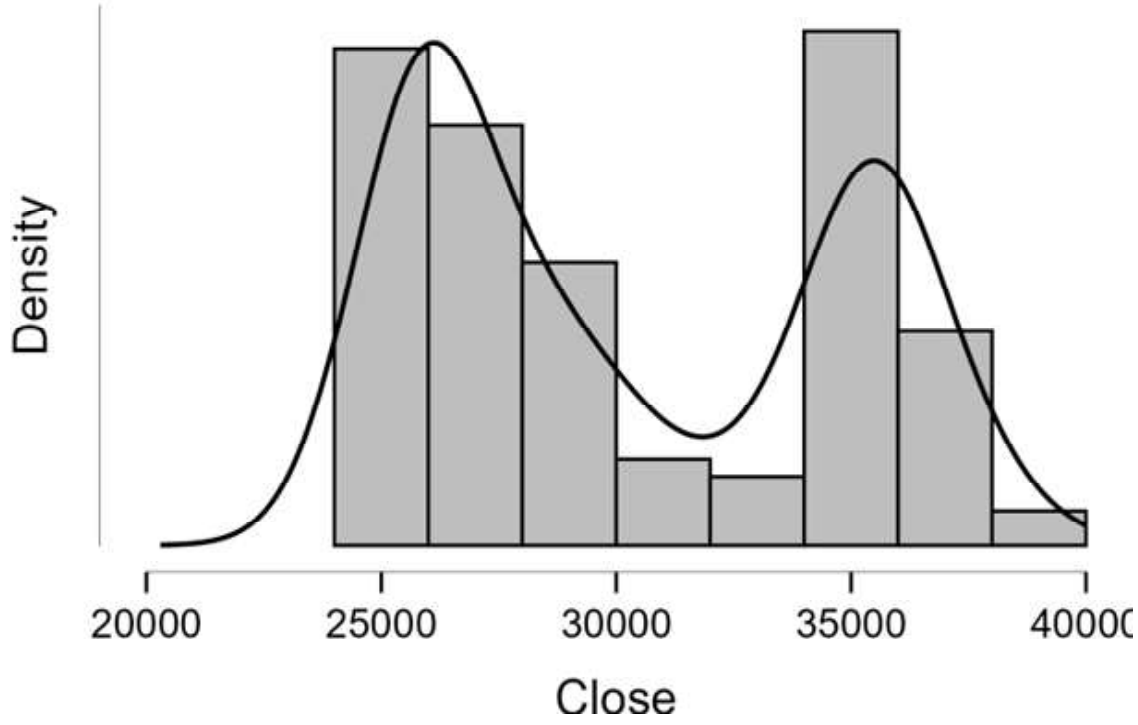
2021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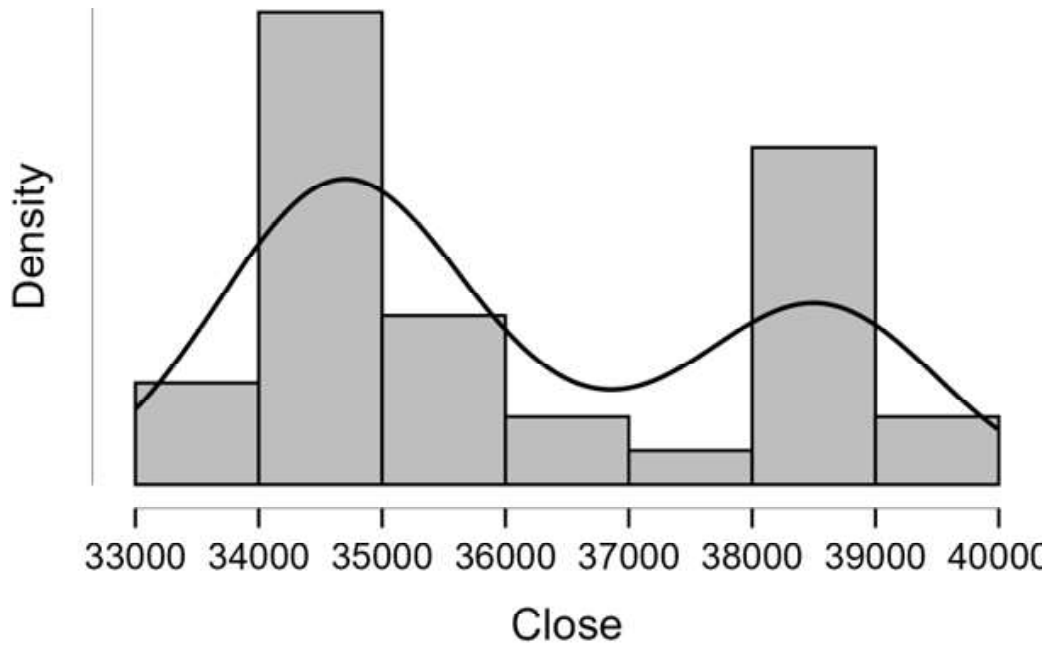

Source: From researcher's data analysis

Table 35 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	0.0679	14.7377	Fréchet	-0.6514	1.5353	Weibull
2011	-0.3845	2.6009	Weibull	-0.1898	5.2692	Weibull
2012	-0.2646	3.7790	Weibull	-0.3289	3.0400	Weibull
2013	-0.0290	34.4963	Weibull	-0.6781	1.4747	Weibull
2014	-0.1637	6.1075	Weibull	-0.5022	1.9913	Weibull
2015	0.0519	19.2749	Fréchet	-0.5399	1.8522	Weibull
2016	-0.5564	1.7973	Weibull	-0.0262	38.1940	Weibull
2017	-0.1729	5.7852	Weibull	-0.3879	2.5781	Weibull
2018	-0.2969	3.3680	Weibull	-0.3353	2.9823	Weibull
2019	-0.3719	2.6891	Weibull	-0.1335	7.4925	Weibull
2020	-0.1398	7.1545	Weibull	-0.5127	1.9504	Weibull
2021	0.4274	2.3396	Fréchet	-0.4799	2.0837	Weibull
2022	0.2518	3.9713	Fréchet	-0.5172	1.9336	Weibull

Source : From researcher's data analysis

Table 36 : Tail index and classification of the Index

	Shape	Scale	Comments based on Index values
2010	7.763094	5449.7	heavy-tailed and moments of higher order exists
2011	4.445153	5087.6	heavy-tailed and moments of higher order exists
2012	9.08175	5489.6	heavy-tailed and moments of higher order exists
2013	4.537388	5972.7	heavy-tailed and moments of higher order exists
2014	6.215296	8675.1	heavy-tailed and moments of higher order exists
2015	14.14891	10798	heavy-tailed and moments of higher order exists
2016	7.74986	9434.6	heavy-tailed and moments of higher order exists
2017	11.85559	9750	heavy-tailed and moments of higher order exists
2018	5.359243	11565.75	heavy-tailed and moments of higher order exists
2019	10.35874	14146.15	heavy-tailed and moments of higher order exists
2020	2.364318	11179.6	heavy-tailed and only mean exists
2021	4.659129	24301.45	heavy-tailed and moments of higher order exists
2022	12.5469	33475.05	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 37 : Index value for Stable Models

	α	β	σ	μ	Model
2010	1.89754	1	303.7098	6167.41677	Stable
2011	2	0	412.7843	6370.8017	Normal
2012	2.0000	0.0000	194.7339	6125.5010	Normal
2013	2	0	776.6828	7496.9265	Normal
2014	2	0	630.229	10203.818	Normal
2015	1.9470	1.0000	321.1494	11569.3635	Stable
2016	2	0	373.3321	10717.7371	Normal
2017	2	0	268.3725	10604.6519	Normal
2018	2	0	823.9118	13945.5188	Normal
2019	1.92243	-1	319.231757	15595.66172	Stable
2020	2	0	2526.45	17305.67	Normal
2021	2	0	3516.583	30375.483	Normal
2022	2	0	1443.912	36110.352	Normal

Source: From researcher's data analysis

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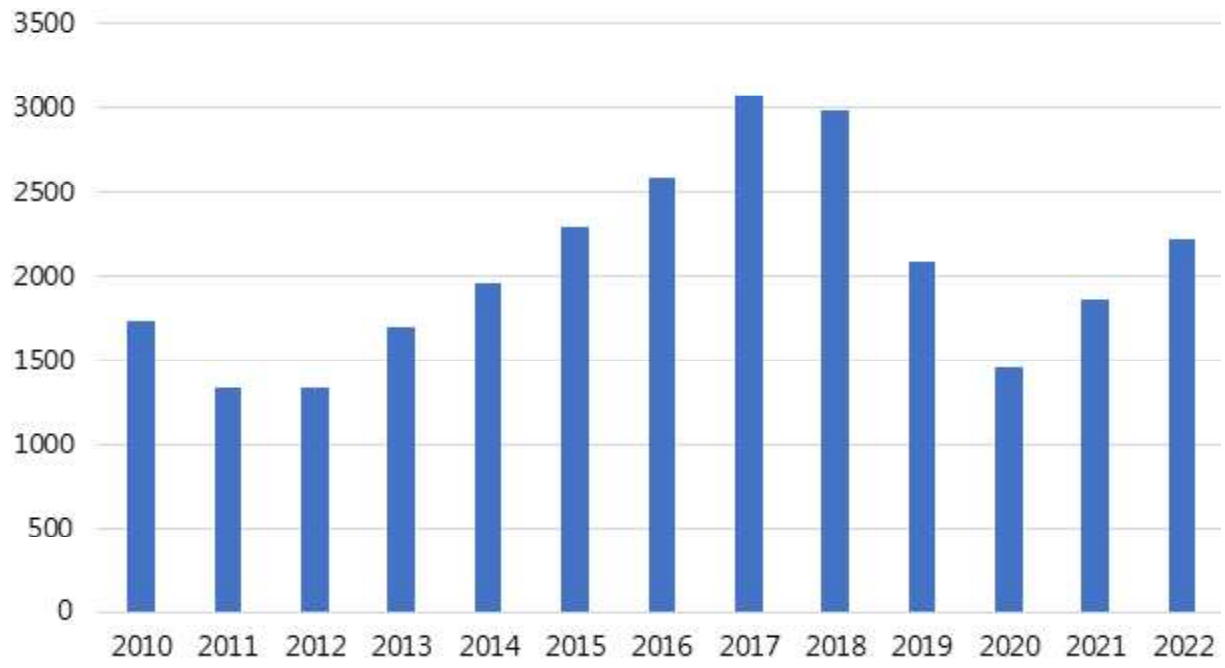
Table 38 : Descriptive Statistics and Test for Normal Probability Model

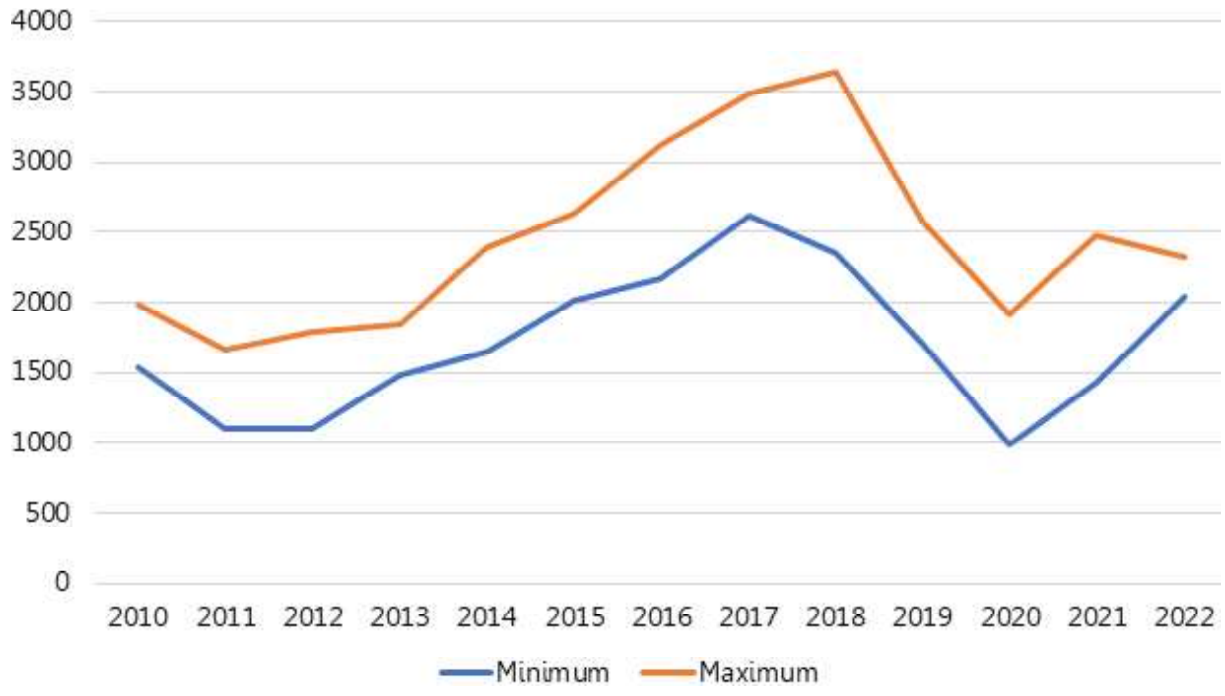
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	246	245	252	247	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	1728.988	1335.064	1344.556	1693.53	1964.399	2298.552	2597.441	3076.177	2987.239	2088.506	1464.13	1863.863	2226.043
Std. Deviation	111.501	122.737	187.705	81.931	201.363	136.486	237.06	158.539	375.948	262.129	238.071	278.657	73.555
Coefficient of Variation	0.064	0.092	0.14	0.048	0.103	0.059	0.091	0.052	0.126	0.126	0.163	0.15	0.033
Skewness	0.583	-0.07	0.877	-0.165	0.521	-0.128	0.229	-0.246	-0.19	0.253	-0.073	0.662	-0.778
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-0.77	-0.689	-0.404	-0.753	-0.686	-0.734	-0.916	0.66	-1.397	-1.316	-0.881	-0.962	0.423
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.924	0.95	0.885	0.98	0.937	0.983	0.96	0.974	0.914	0.922	0.969	0.88	0.944
P-value of Shapiro-Wilk	< .001	< .001	< .001	0.002	< .001	0.004	< .001	< .001	< .001	< .001	< .001	< .001	0.063
Minimum	1534.4	1100.6	1108.3	1484	1655.1	2008.6	2165.9	2618.4	2348.3	1707.25	987.2	1430.85	2035.2
Maximum	1981	1668.7	1788.9	1848.4	2387.3	2633	3127.8	3480.5	3642.7	2574.15	1909	2473.05	2328.3

Source: From researcher's data analysis



Graph 19 : Mean Values of the Index

Source: From researcher's data analysis

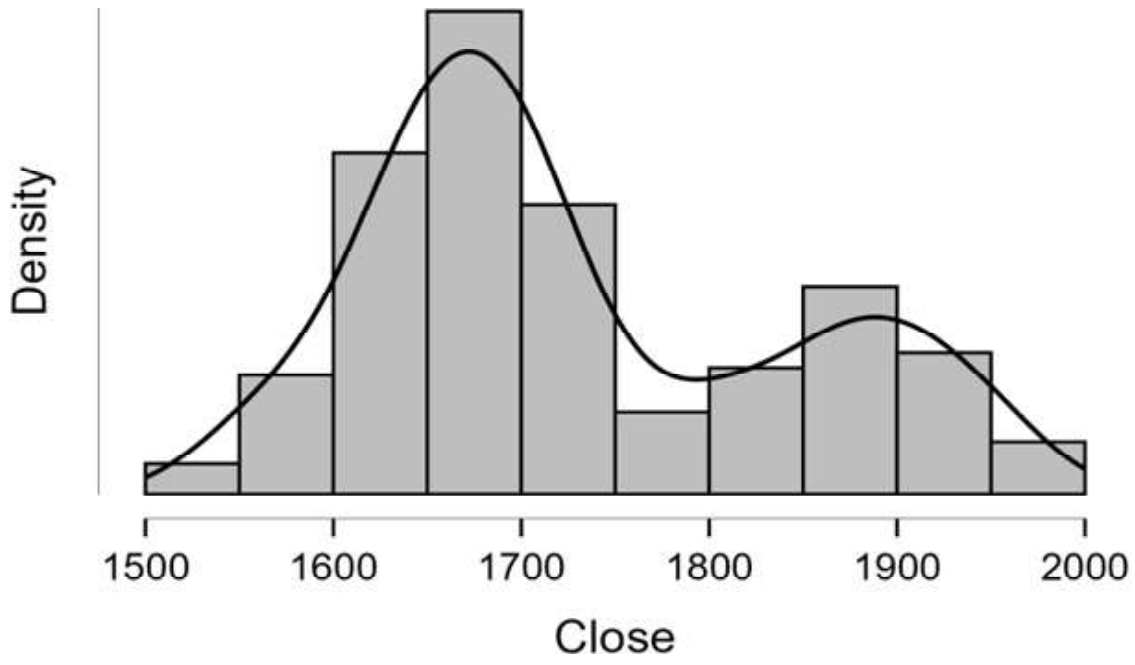


Graph 20 : Maximum and Minimum values of the index

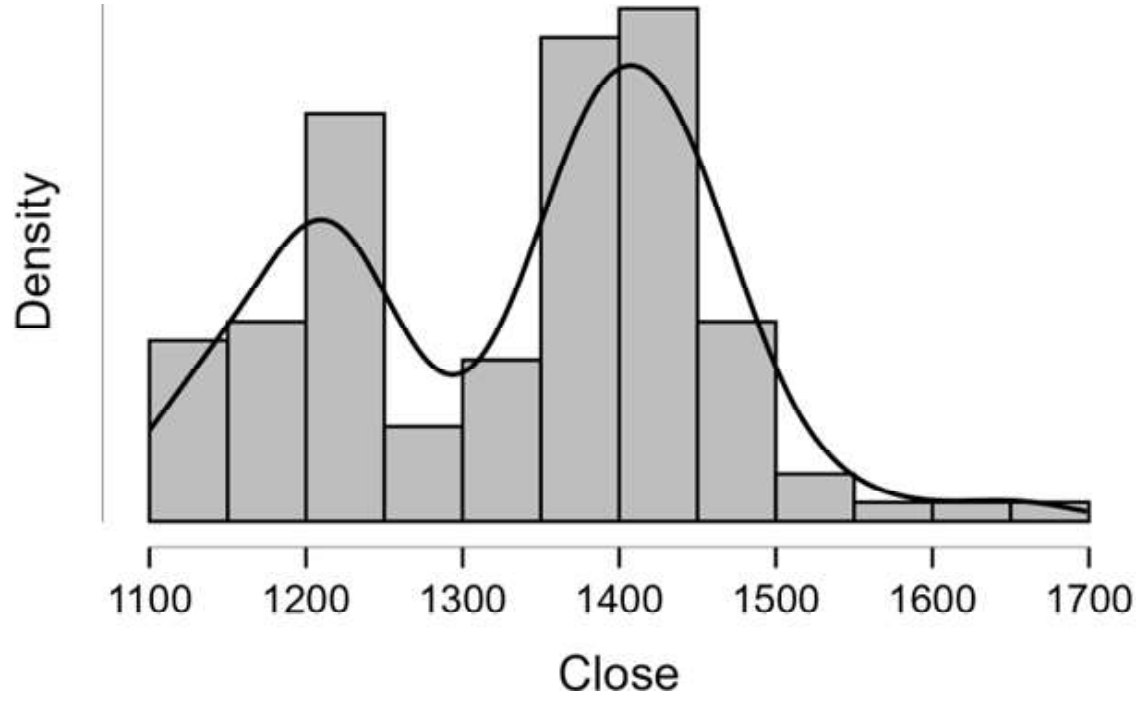
Source: From researcher's data analysis

Distribution Plots

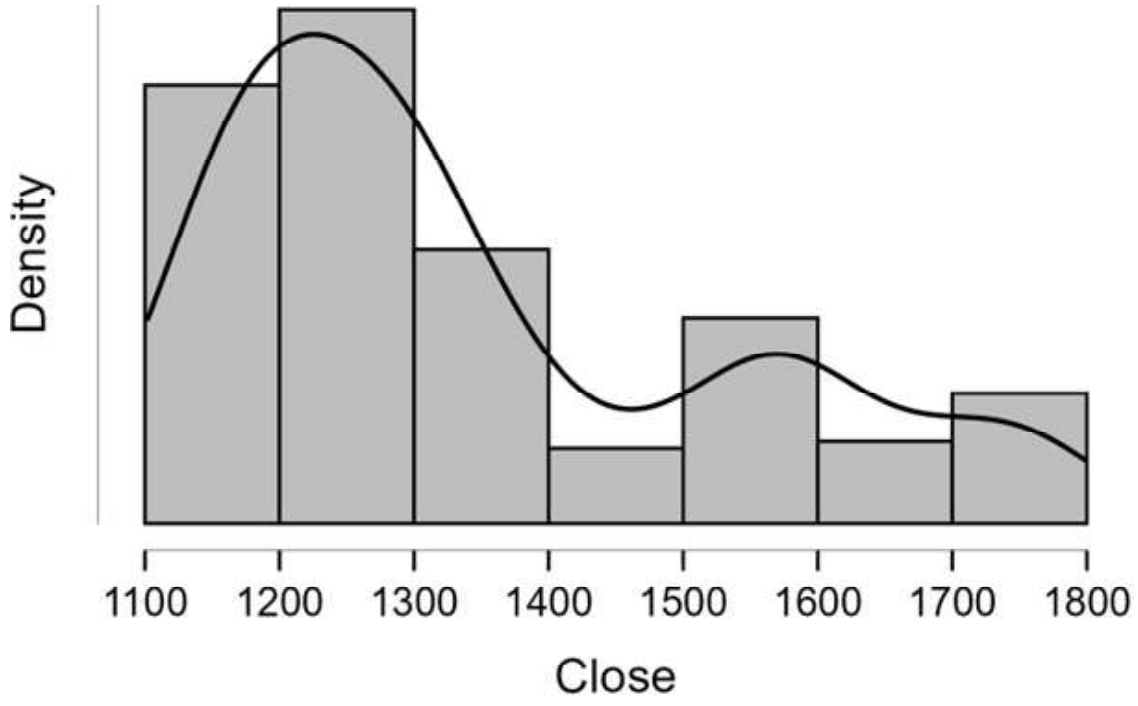
2010



2011



2012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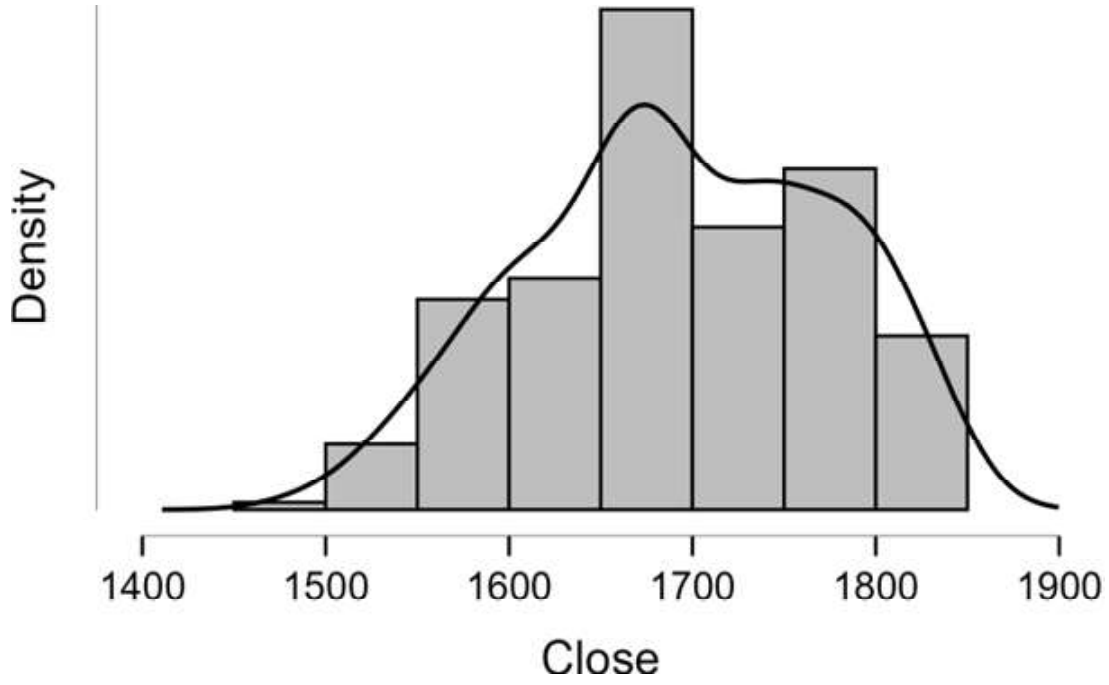
1400
1500
1600
1700
1800
Close

2013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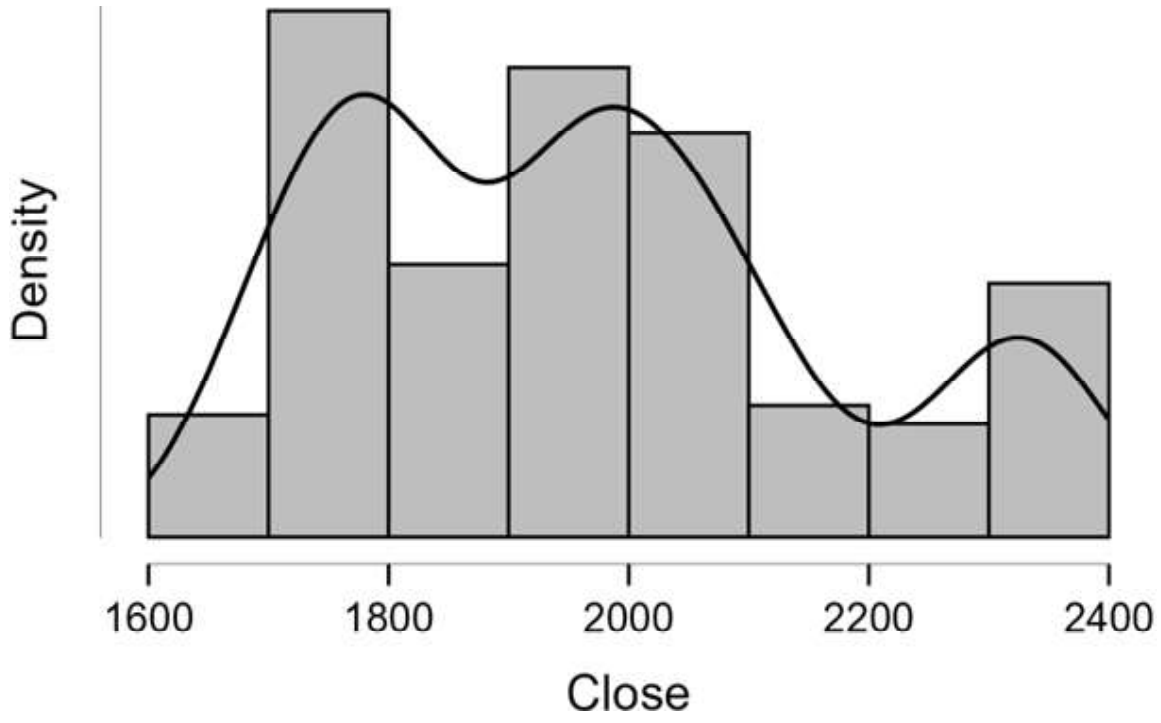
1700
1800
1900
Close

2014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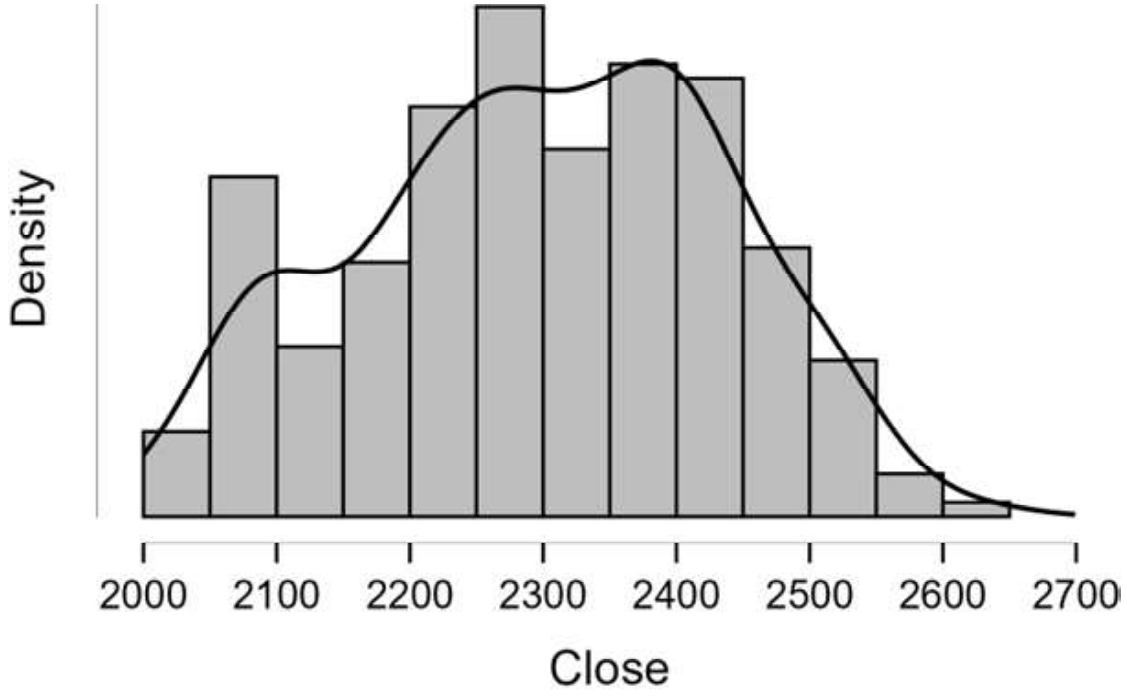
2400
Close

2015


Density
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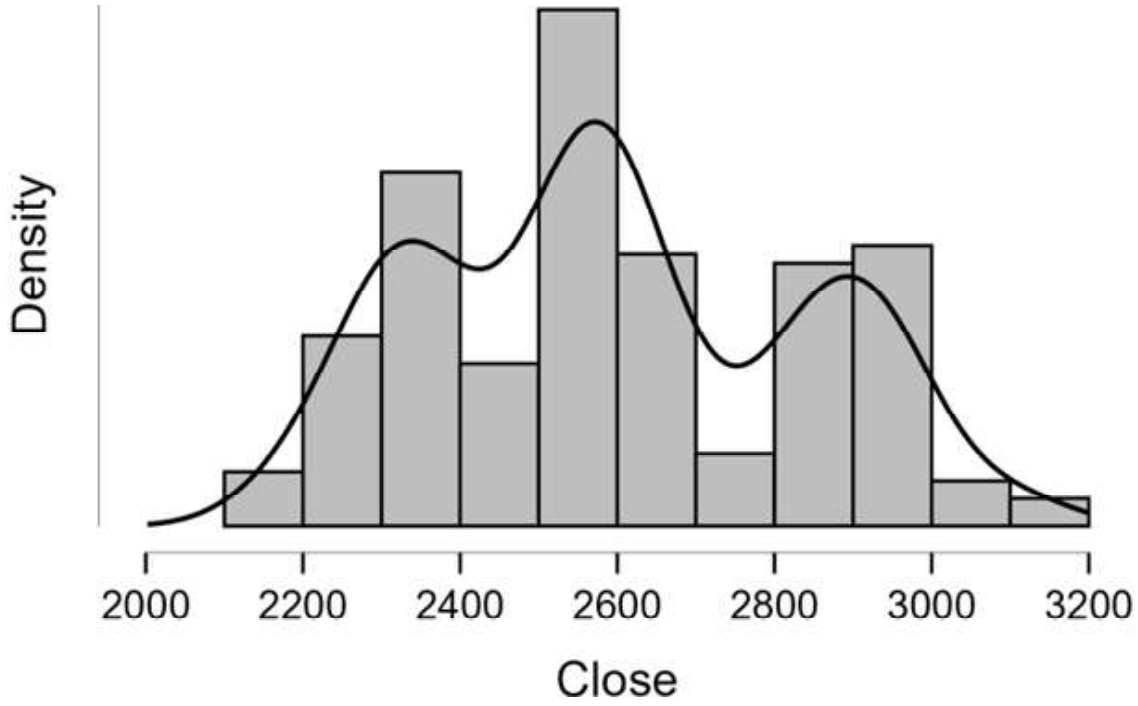
2200
2300
2400
2500
2600
2700
Close

2016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2400
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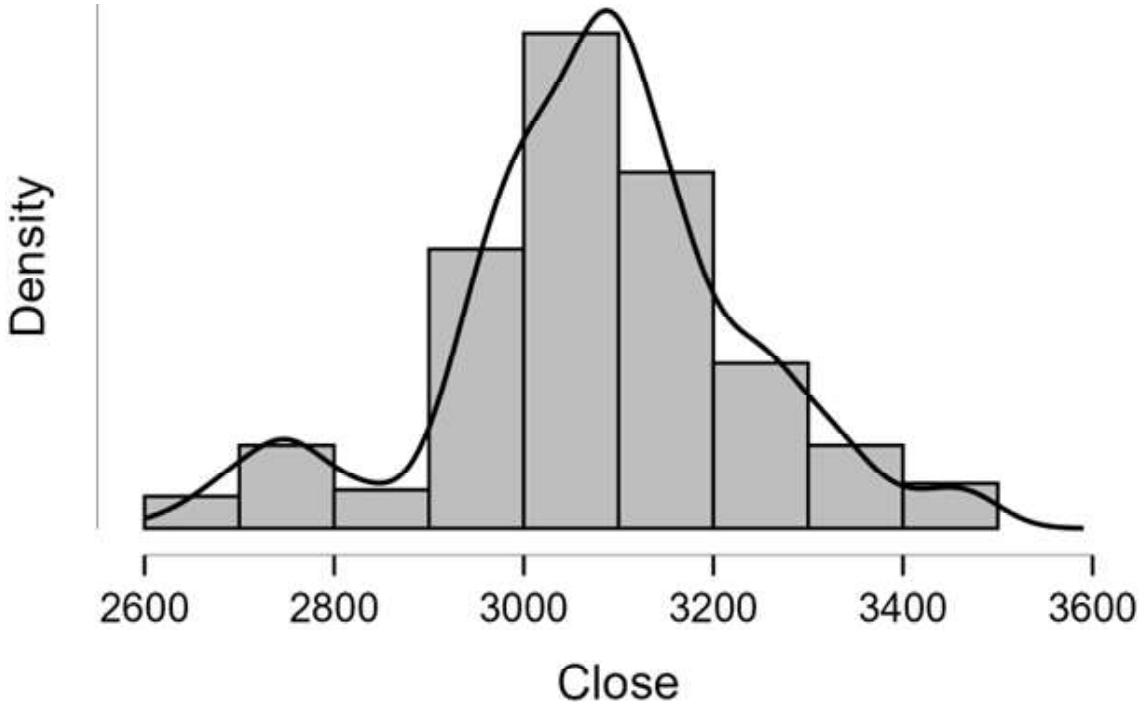
2800
3000
3200
Close

2017


Density
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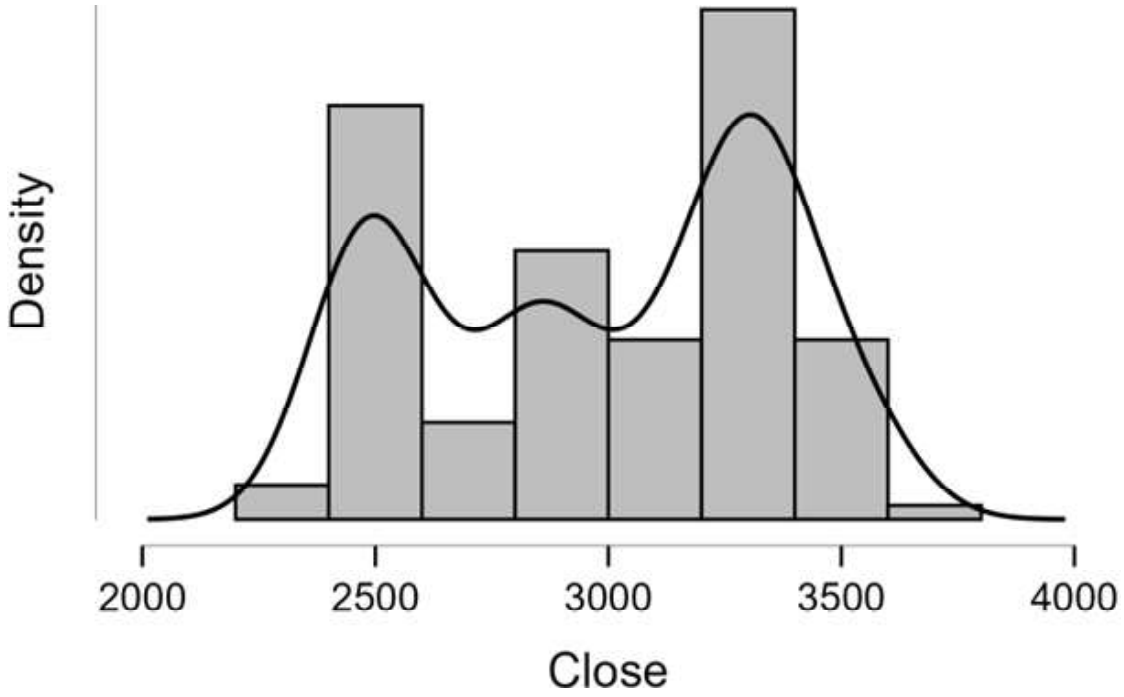
3000
3200
3400
3600
Close

2018


Density
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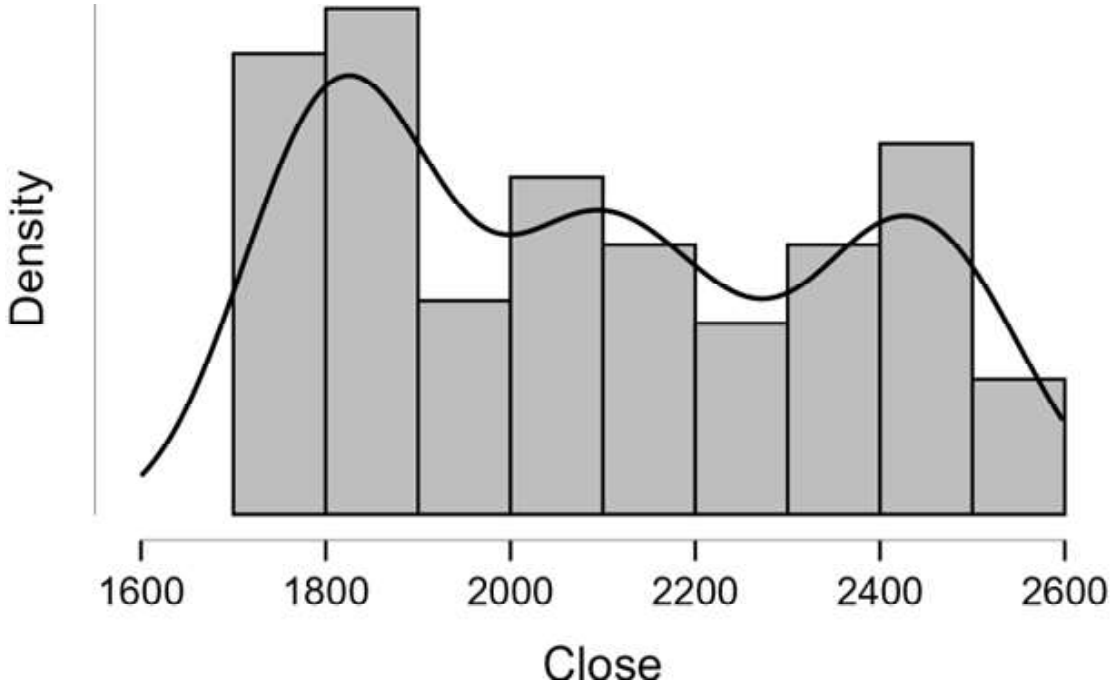
2500
3000
3500
4000
Close

2019


Density
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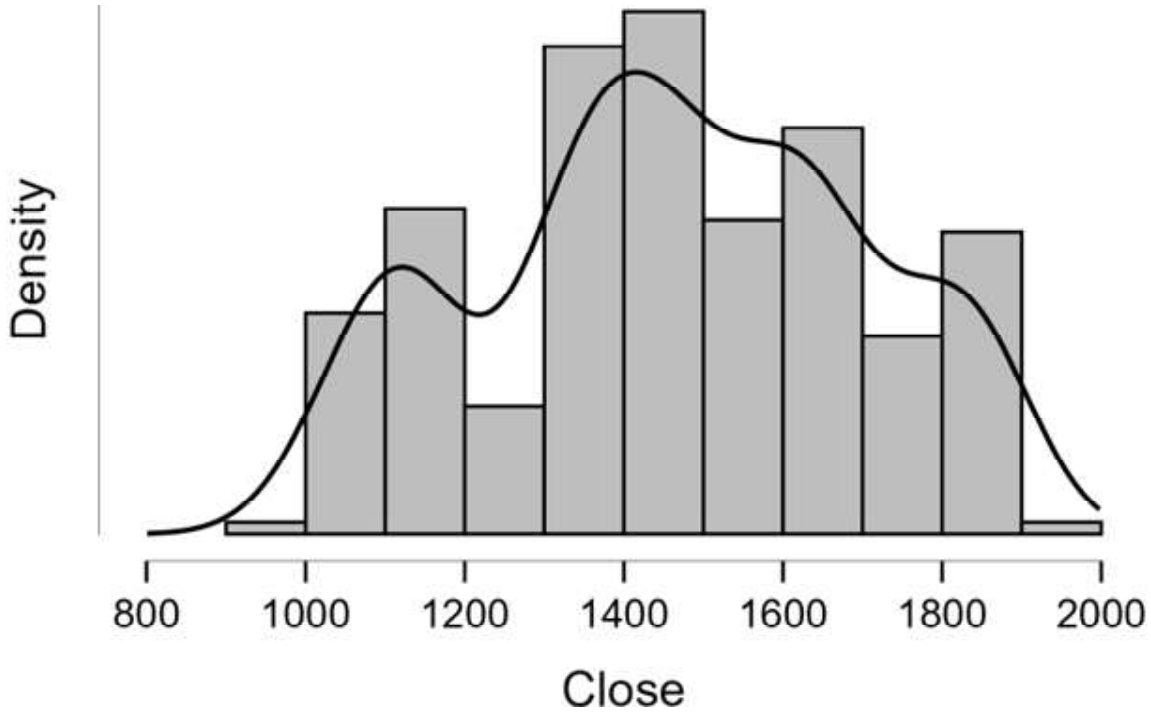
2400
2600
Close

2020


Density
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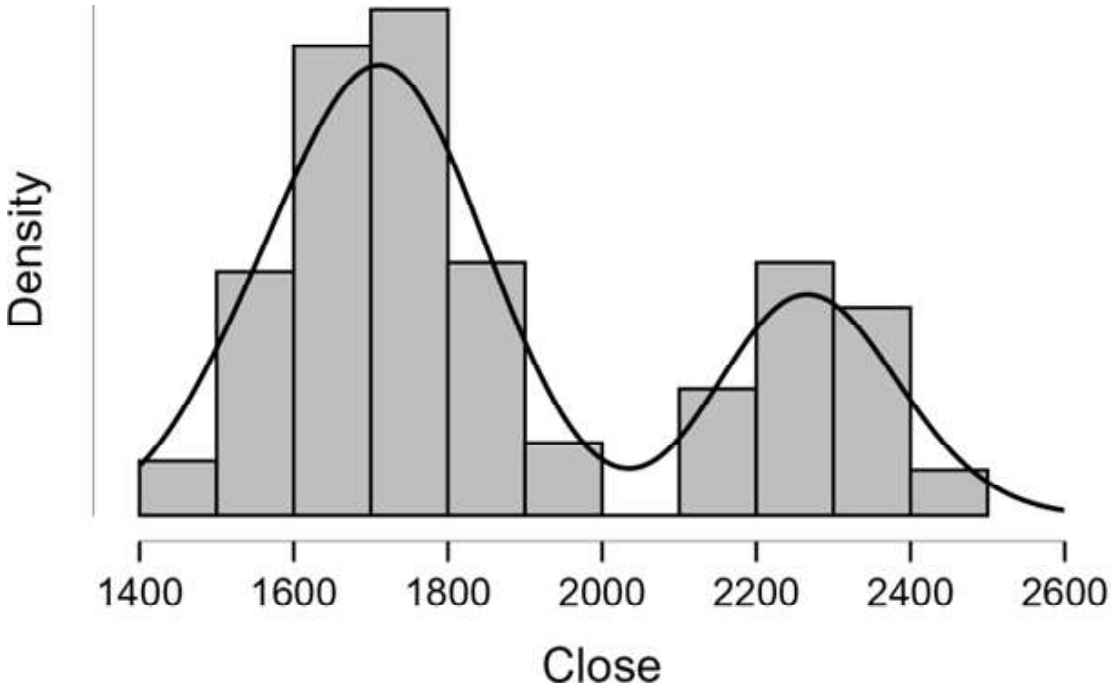
2000
Close

2021


Density
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2000
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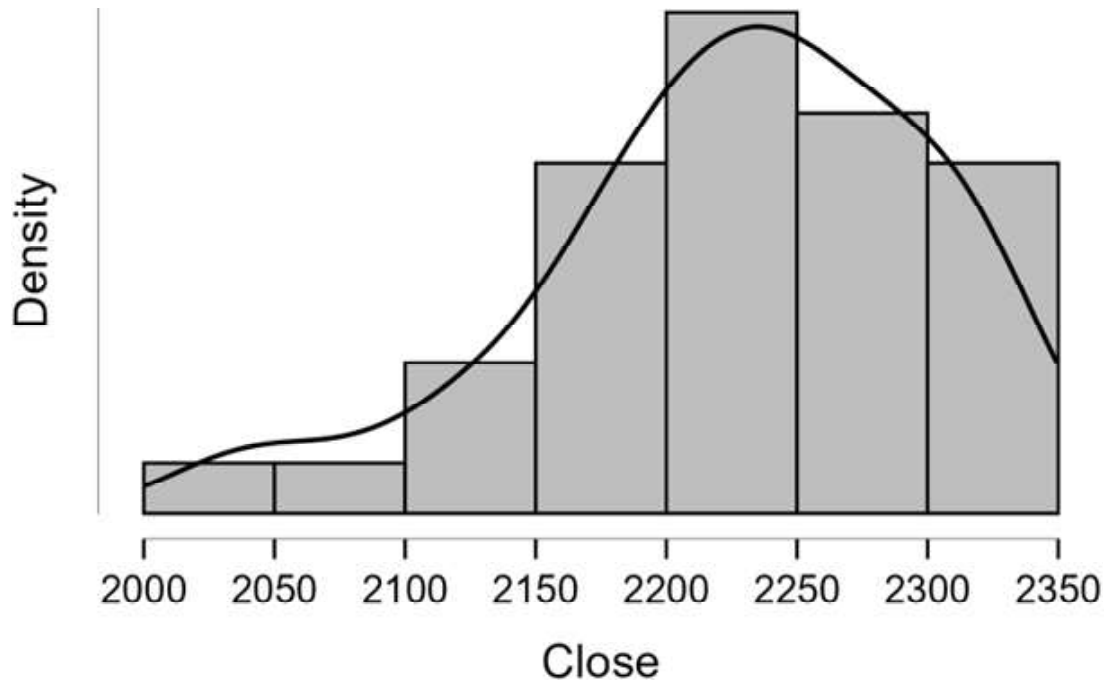
2400
2600
Close



Source: From researcher's data analysis

Table 39 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.0019	518.0918	Weibull	-0.5323	1.8786	Weibull
2011	-0.2679	3.7325	Weibull	-0.3385	2.9538	Weibull
2012	0.3054	3.2740	Fréchet	-0.8105	1.2337	Weibull
2013	-0.4376	2.2853	Weibull	-0.2396	4.1728	Weibull
2014	-0.0220	45.4915	Weibull	-0.6394	1.5640	Weibull
2015	-0.3165	3.1593	Weibull	-0.2794	3.5791	Weibull
2016	-0.2202	4.5423	Weibull	-0.4681	2.1365	Weibull
2017	-0.3037	3.2930	Weibull	-0.2177	4.5933	Weibull
2018	-0.5328	1.8770	Weibull	-0.3188	3.1366	Weibull
2019	-0.1603	6.2399	Weibull	-0.7231	1.3828	Weibull
2020	-0.4034	2.4790	Weibull	-0.3209	3.1161	Weibull
2021	0.1493	6.6958	Fréchet	-0.6334	1.5788	Weibull
2022	-0.7223	1.3844	Weibull	-0.0091	110.1431	Weibull

Source: From researcher's data analysis

Table 40 : Tail index and classification of the Index

	Shape	Scale	Comments based on the index values
2010	8.389719	1534.4	heavy-tailed and moments of higher order exists
2011	5.215221	1100.6	heavy-tailed and moments of higher order exists
2012	5.350913	1108.3	heavy-tailed and moments of higher order exists
2013	7.523621	1484	heavy-tailed and moments of higher order exists
2014	5.925238	1655.1	heavy-tailed and moments of higher order exists
2015	7.402473	2008.6	heavy-tailed and moments of higher order exists
2016	5.547416	2165.9	heavy-tailed and moments of higher order exists
2017	6.164066	2618.4	heavy-tailed and moments of higher order exists
2018	4.235886	2348.3	heavy-tailed and moments of higher order exists
2019	5.083042	1707.25	heavy-tailed and moments of higher order exists
2020	2.589776	987.2	heavy-tailed and only mean exists
2021	3.881735	1430.85	heavy-tailed and moments of higher order exists
2022	10.39733	2035.2	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 41 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	80.0793	1730.90485	Normal
2011	2	0	91.5175	1334.68971	Normal
2012	1.7693	1.0000	118.8344	1307.9570	Stable
2013	2	0	61.1362	1693.21089	Normal
2014	2	0	145.692	1967.315	Normal
2015	2.0000	0.0000	101.5150	2298.0670	Normal
2016	2	0	178.291	2598.8415	Normal
2017	1.46713	-0.2659	85.8877	3089.37266	Stable
2018	2	0	292.712	2985.4205	Normal
2019	2	0	202.627	2090.1667	Normal
2020	2	0	178.952	1463.6773	Normal
2021	2	0	200.228	1869.4066	Normal
2022	1.88652	-1	47.9826	2232.6316	Stable

Source: From researcher's data analysis

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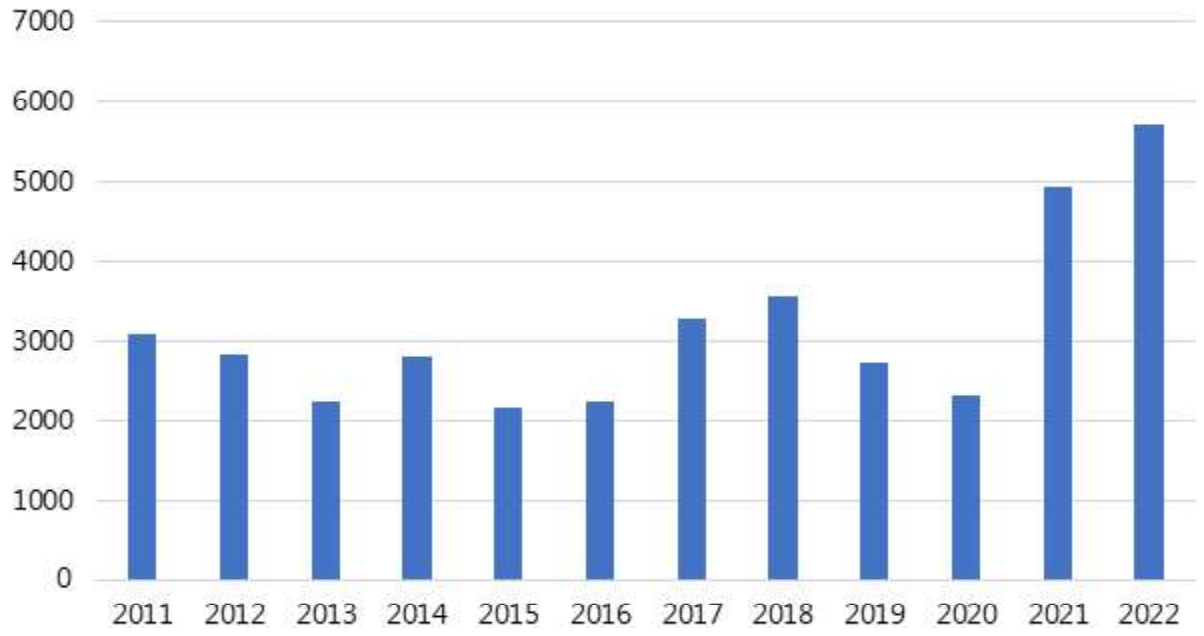
Table 42 : Descriptive Statistics and Test for Normal Probability Model

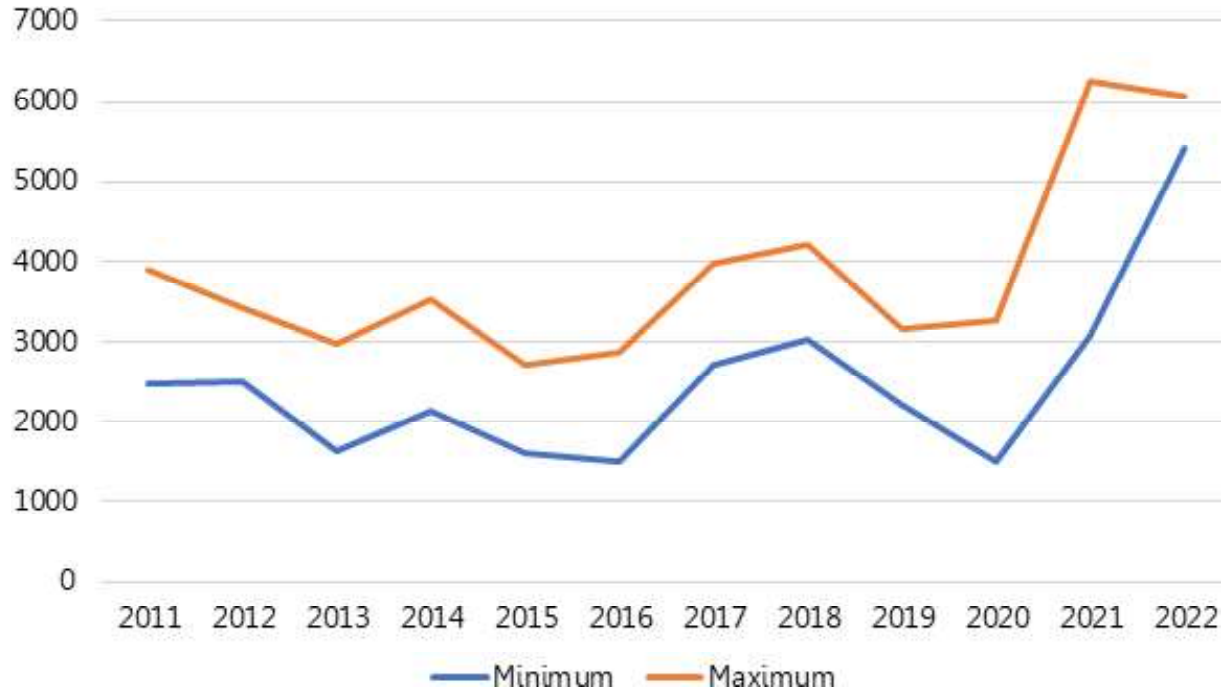
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	116	251	250	244	248	247	248	246	245	252	247	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean	3095.876	2837.996	2247.878	2801.391	2155.694	2231.37	3288.716	3567.859	2737.444	2310.683	4943.269	5729.455
Std. Deviation	385.463	196.77	295.038	386.095	324.386	398.075	346.813	286.334	252.553	447.901	855.208	156.051
Coefficient of Variation	0.125	0.069	0.131	0.138	0.15	0.178	0.105	0.08	0.092	0.194	0.173	0.027
Skewness	0.518	0.864	0.481	0.044	-0.164	-0.138	0.474	0.333	-0.338	0.185	-0.793	-0.107
Std. Error of Skewness	0.225	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-0.385	0.21	0.066	-1.274	-1.528	-1.389	-1.17	-0.581	-1.122	-0.713	-0.866	-0.187
Std. Error of Kurtosis	0.446	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.947	0.935	0.967	0.945	0.893	0.923	0.906	0.971	0.943	0.976	0.85	0.976
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	0.605
Minimum	2464.6	2495.1	1628.2	2142.5	1605.4	1495.6	2705.2	3036.25	2203.6	1496.45	3077.45	5420.45
Maximum	3902.4	3429.3	2986	3521.8	2715.4	2870	3959.9	4195.75	3149.9	3271.75	6253.1	6059.45

Source: From researcher's data analysis



Graph 21 : Mean Values of the Index

Source: From researcher's data analysis

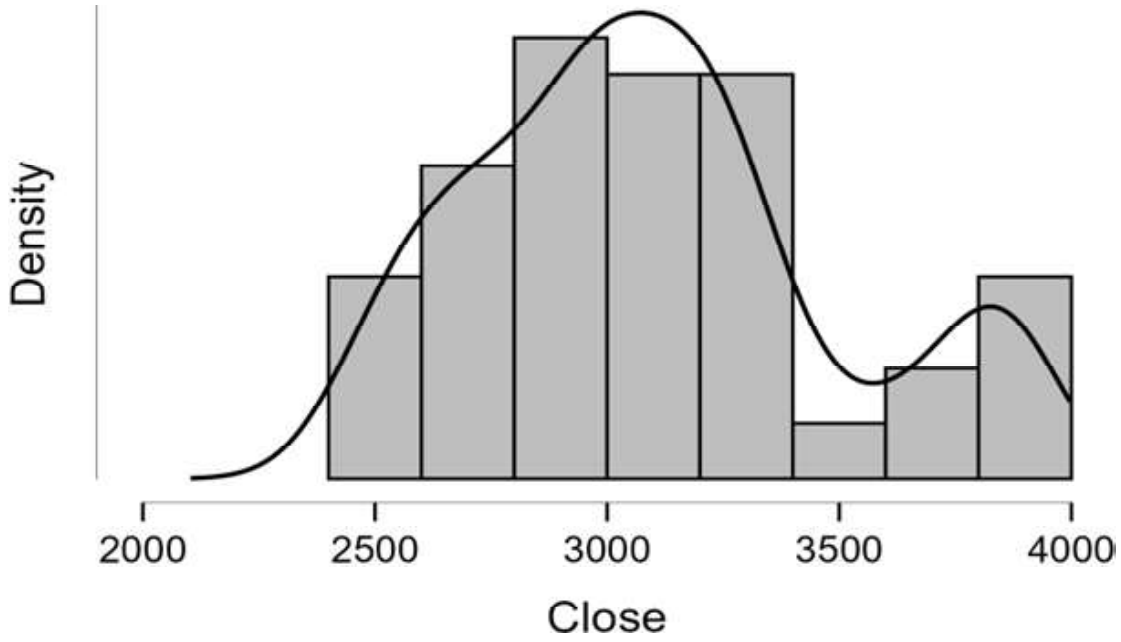


Graph 22 : Maximum and Minimum Values of the Index

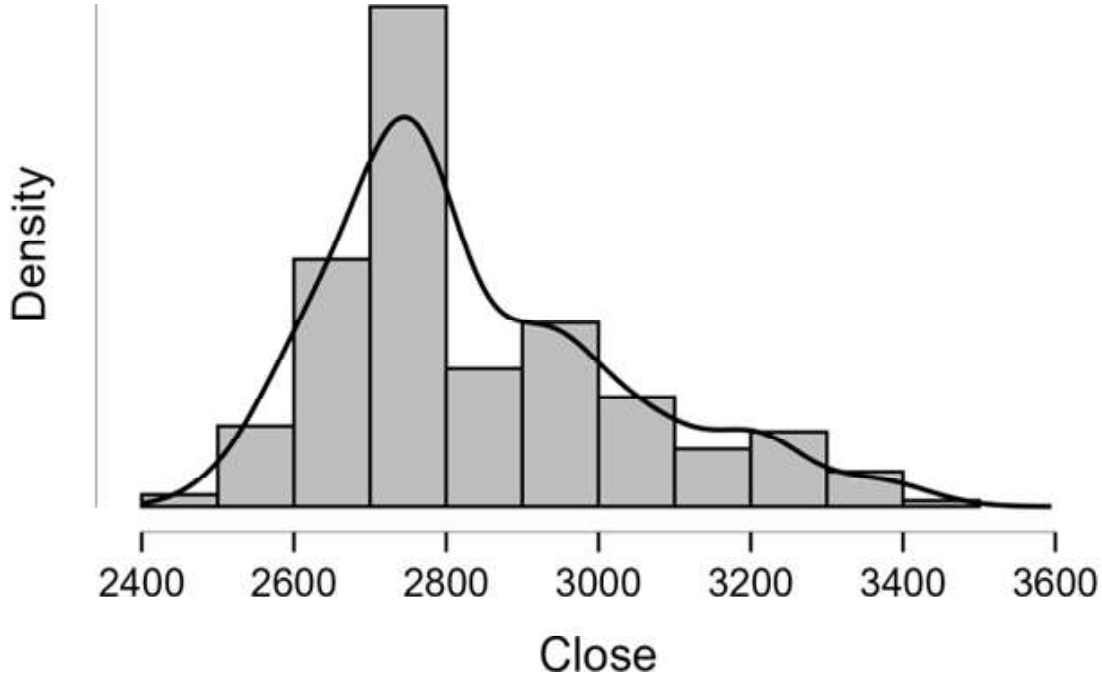
Source: From researcher's data analysis

Distribution Plots

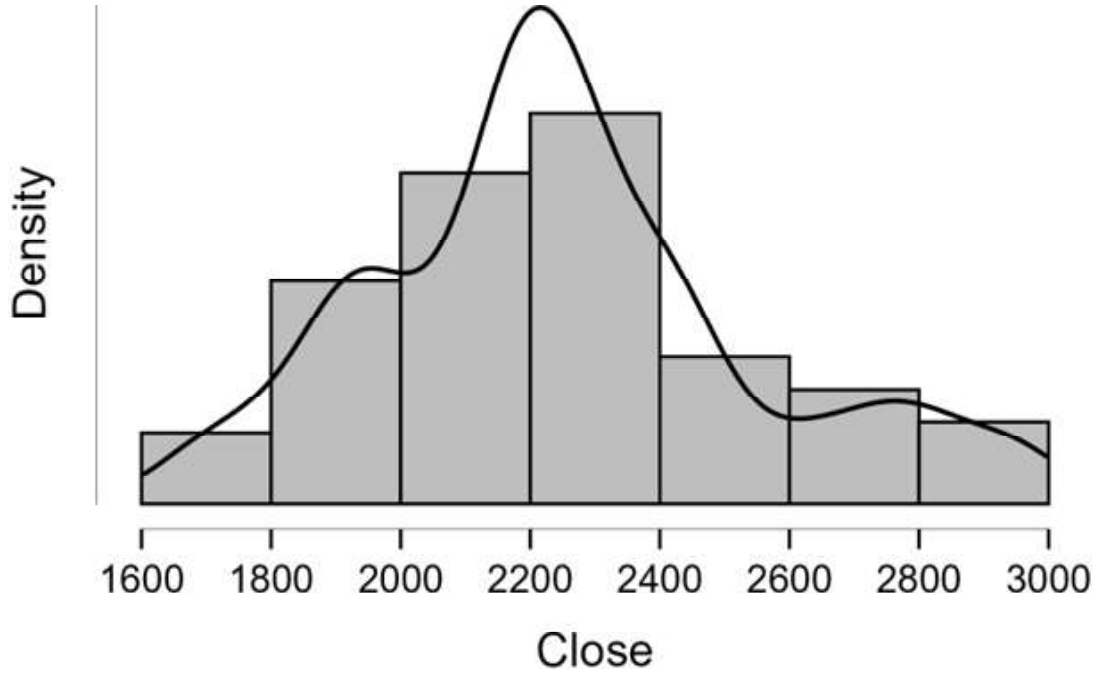
2011



2012



2013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2200
2400
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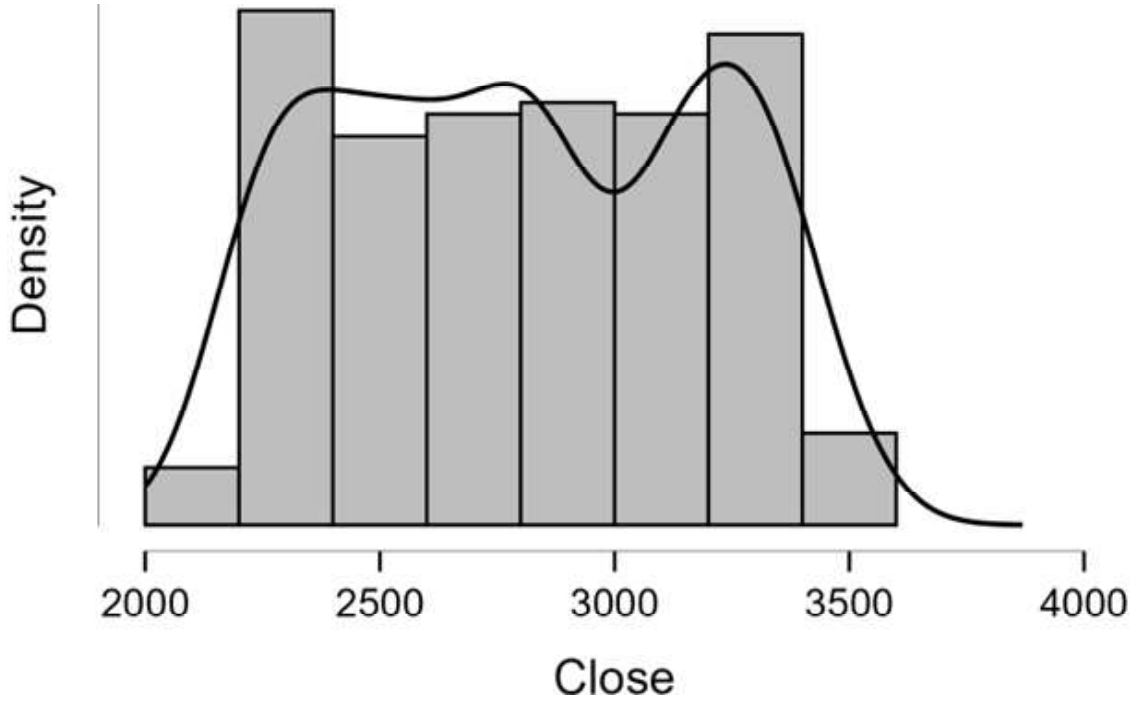
2800
3000
Close

2014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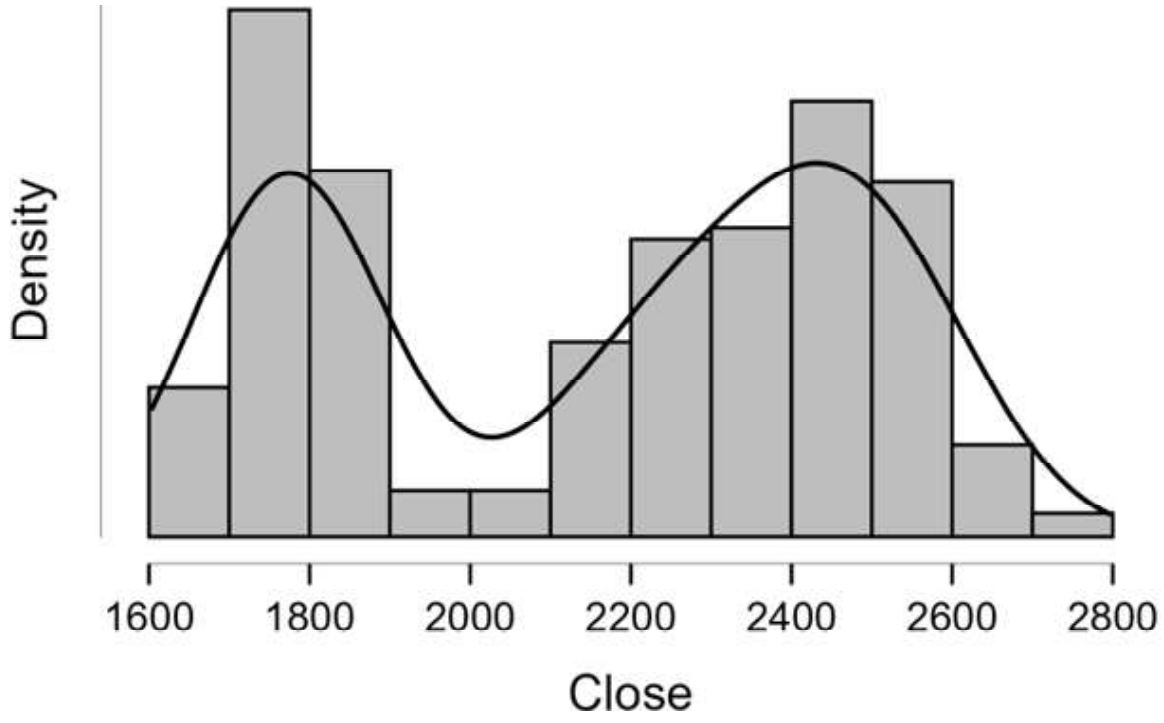
2015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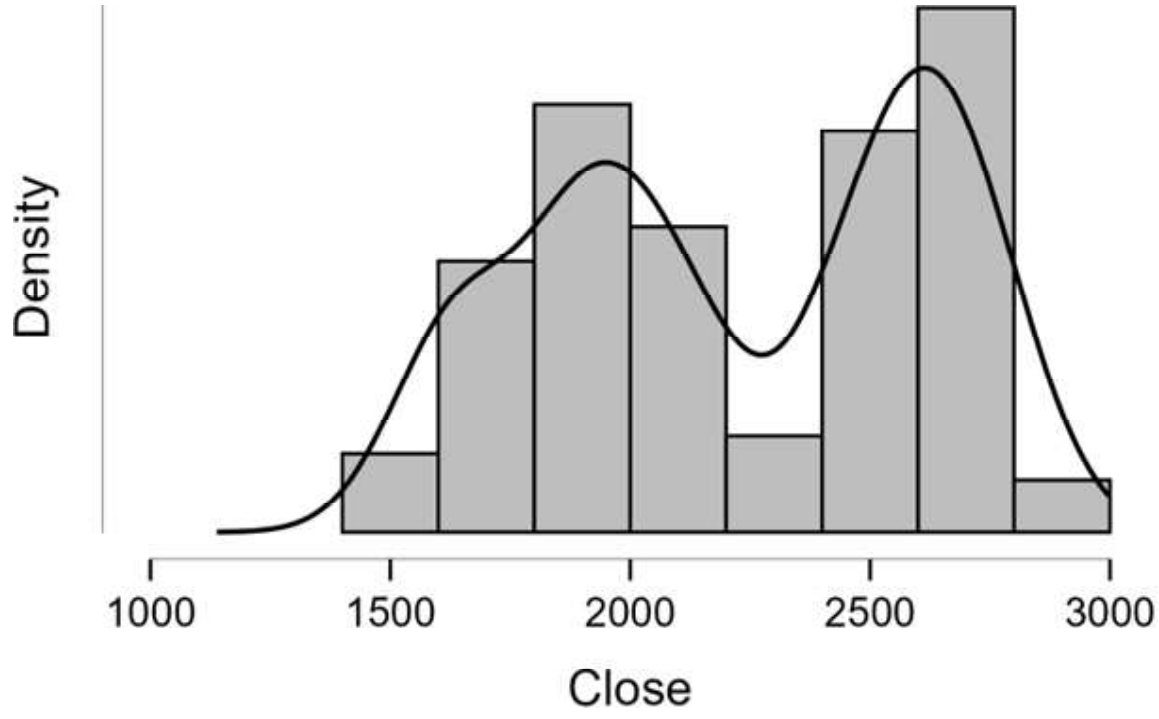
2016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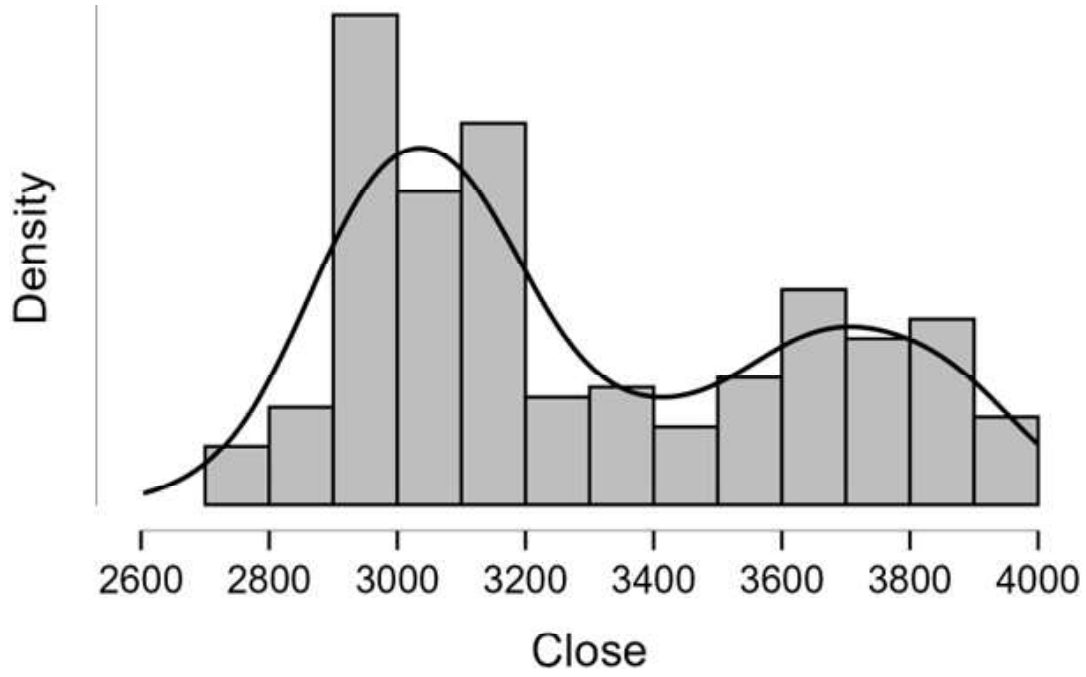
2017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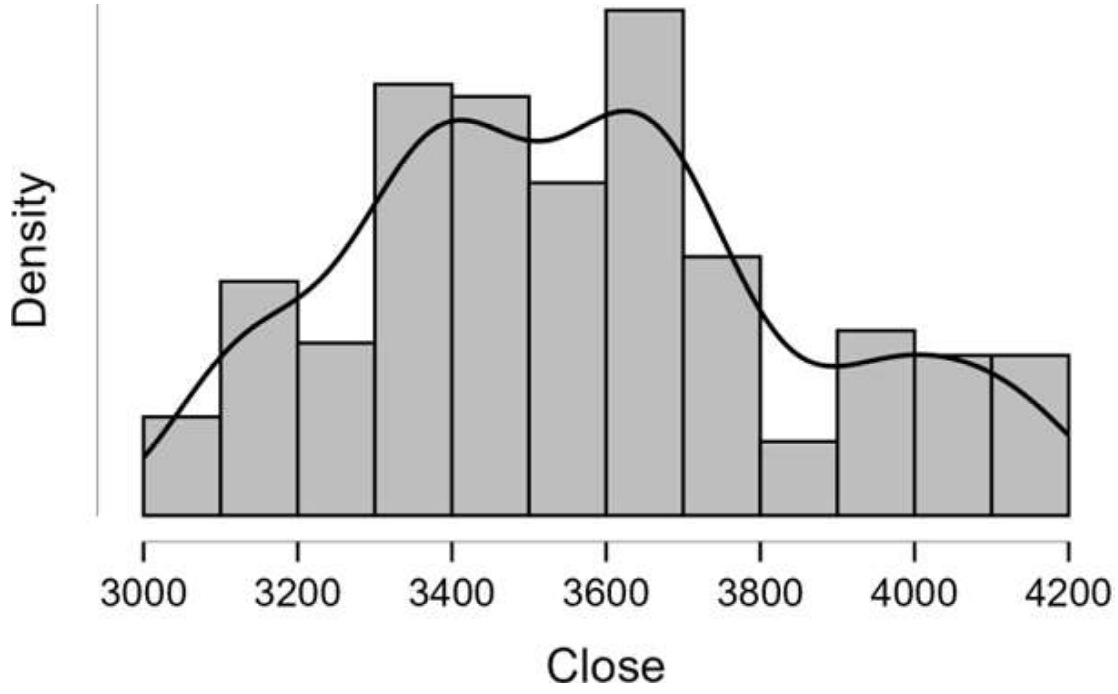
2018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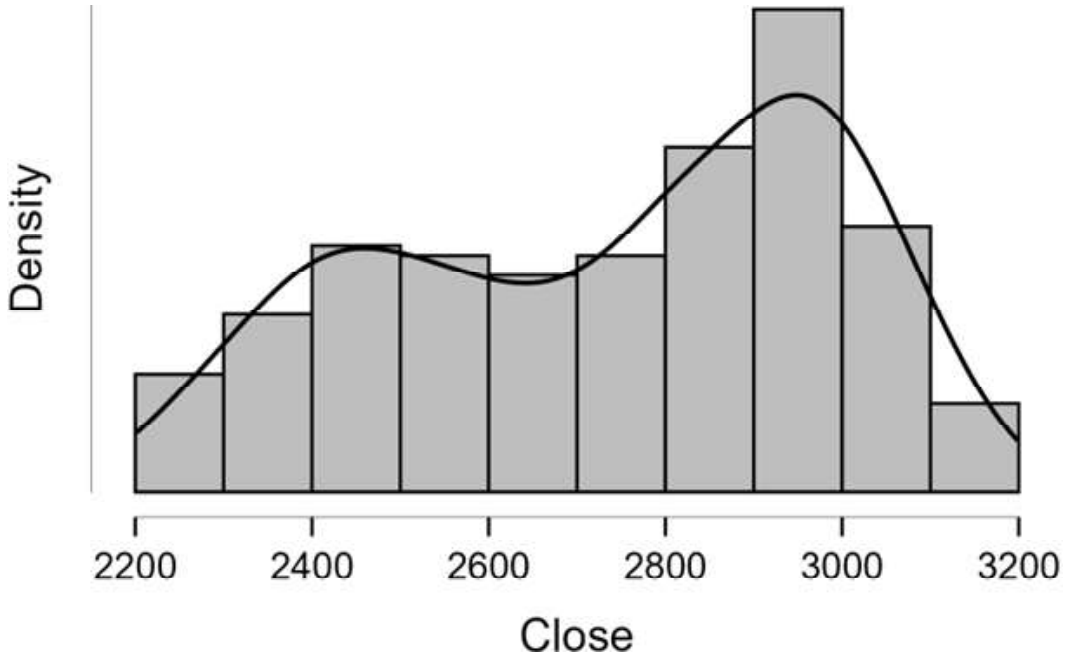
2019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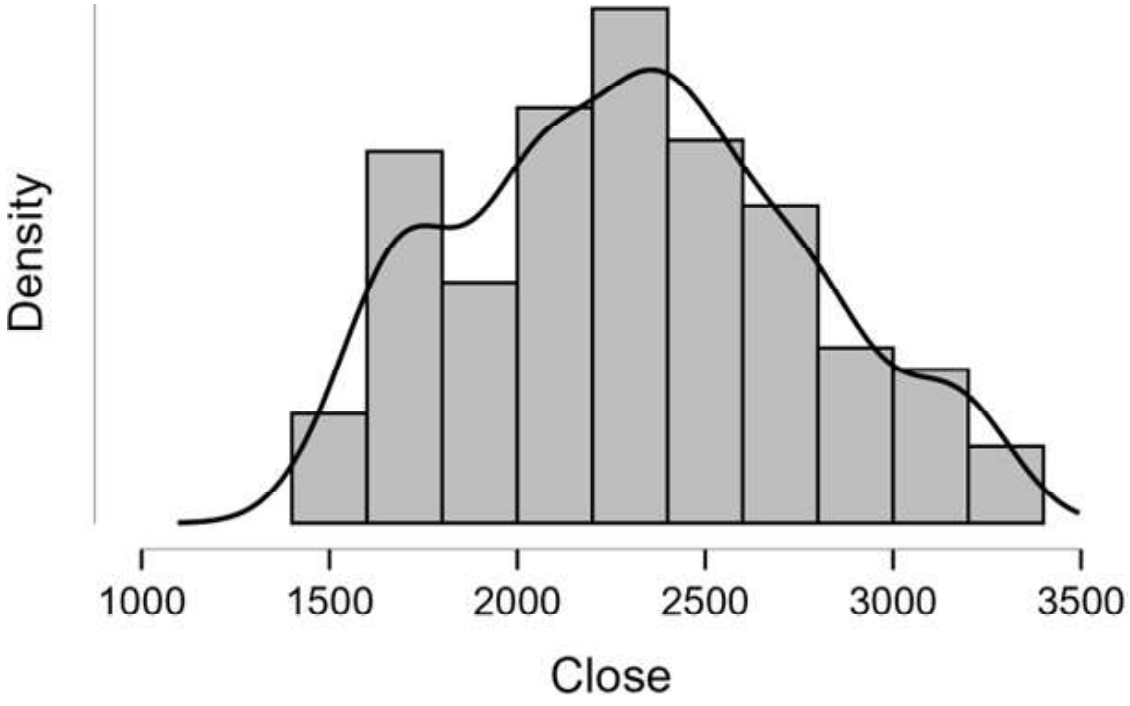
2020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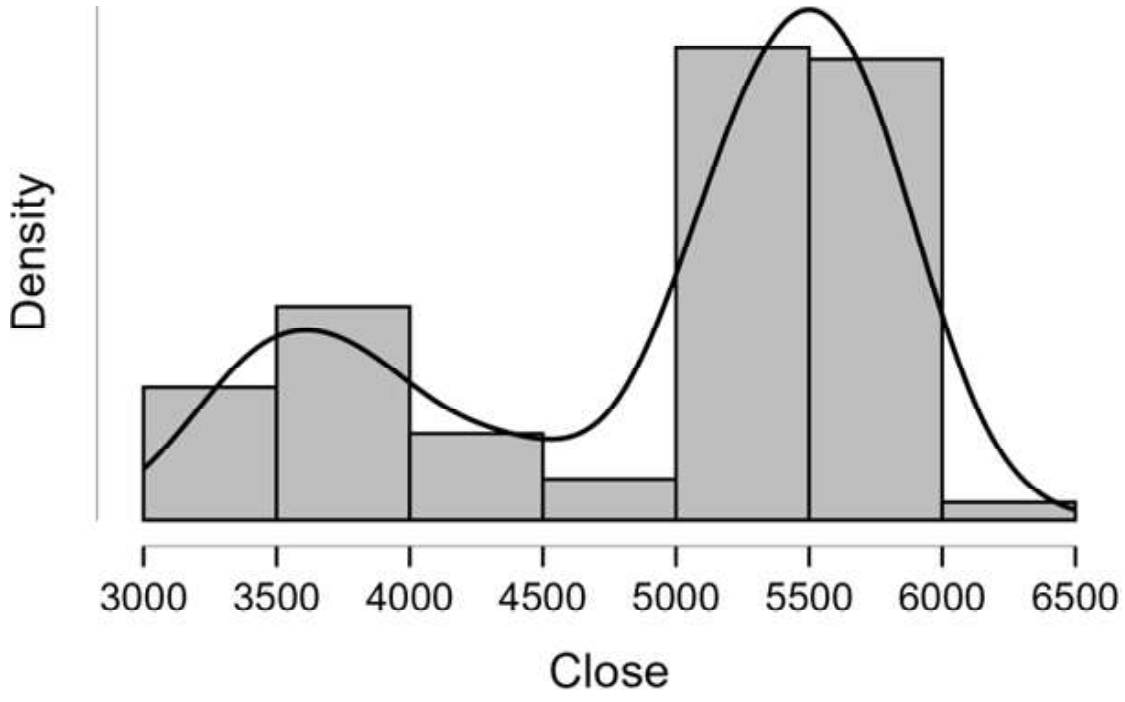
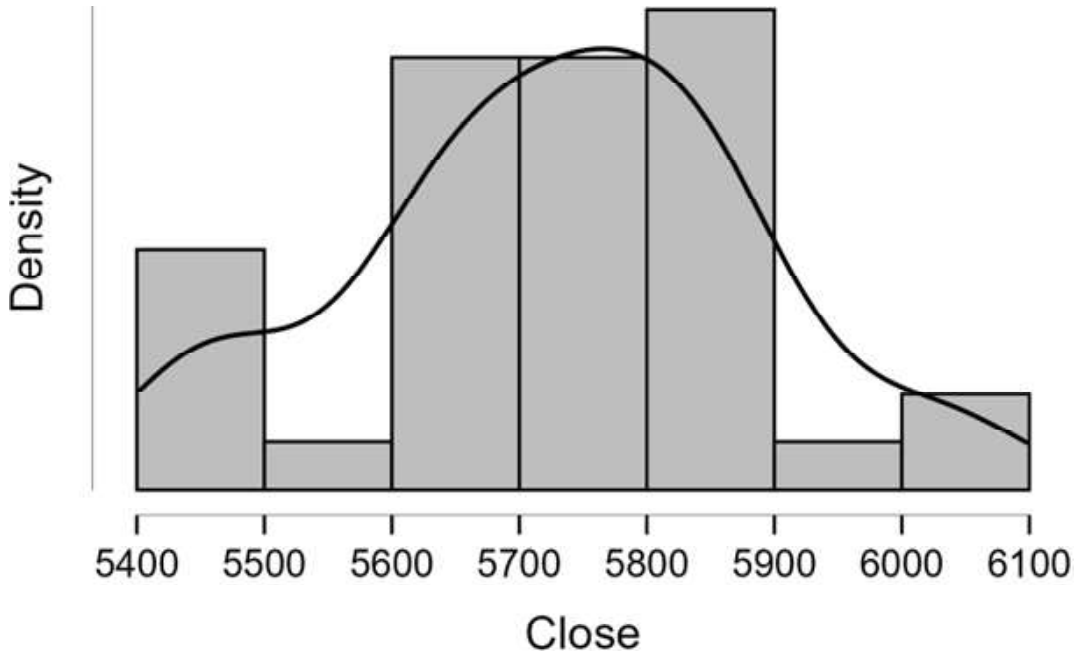
2021



2022



Source: From researcher's data analysis

Table 43 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010						
2011	-0.0970	10.3055	Weibull	-0.5463	1.8304	Weibull
2012	0.0324	30.8291	Fréchet	-0.5190	1.9266	Weibull
2013	-0.1504	6.6496	Weibull	-0.4092	2.4436	Weibull
2014	-0.4186	2.3892	Weibull	-0.5092	1.9639	Weibull
2015	-0.5398	1.8526	Weibull	-0.5478	1.8255	Weibull
2016	-0.5962	1.6774	Weibull	-0.3424	2.9207	Weibull
2017	0.0833	12.0114	Fréchet	-0.5542	1.8044	Weibull
2018	-0.1769	5.6541	Weibull	-0.4673	2.1399	Weibull
2019	-0.5826	1.7165	Weibull	-0.0942	10.6119	Weibull
2020	-0.2409	4.1512	Weibull	-0.4448	2.2482	Weibull
2021	-0.6109	1.6369	Weibull	0.2902	3.4456	Fréchet
2022	-0.3172	3.1529	Weibull	-0.2818	3.5492	Weibull

Source: From researcher's data analysis

Table 44 : Tail index and classification of the Index

	Shape	Scale	Comments based on the index values
2010	-	-	heavy-tailed and moments of higher order exists
2011	4.405461	2464.6	heavy-tailed and moments of higher order exists
2012	7.789774	2495.1	heavy-tailed and moments of higher order exists
2013	3.13658	1628.2	heavy-tailed and moments of higher order exists
2014	3.80911	2142.5	heavy-tailed and moments of higher order exists
2015	3.479475	1605.4	heavy-tailed and moments of higher order exists
2016	2.568373	1495.6	heavy-tailed and only mean exists
2017	5.187276	2705.2	heavy-tailed and moments of higher order exists
2018	6.228015	3036.25	heavy-tailed and moments of higher order exists
2019	4.631939	2203.6	heavy-tailed and moments of higher order exists
2020	2.371836	1496.45	heavy-tailed and only mean exists
2021	2.155215	3077.45	heavy-tailed and only mean exists
2022	16.81756	5420.45	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 45 : Index value for Stable Models

	α	β	σ	μ	Model
2010					Stable
2011	1.98459	0	270.18638	3102.137835	Stable
2012	1.7916	1.0000	124.0398	2806.9631	Stable
2013	1.85623	0.94656	193.5061	2214.238109	Stable
2014	2	0	299.0277	2801.8186	Normal
2015	2.0000	0.0000	254.9189	2154.3381	Normal
2016	2	0	310.7406	2230.0521	Normal
2017	2	0	261.3811	3293.1065	Normal
2018	2	0	208.2906	3570.4368	Normal
2019	2	0	192.0432	2735.2575	Normal
2020	2	0	332.0821	2312.7417	Normal
2021	1.90621	-1	583.05217	5004.797611	Stable
2022	2	0	109.981	5728.933	Normal

Source: From researcher's data analysis

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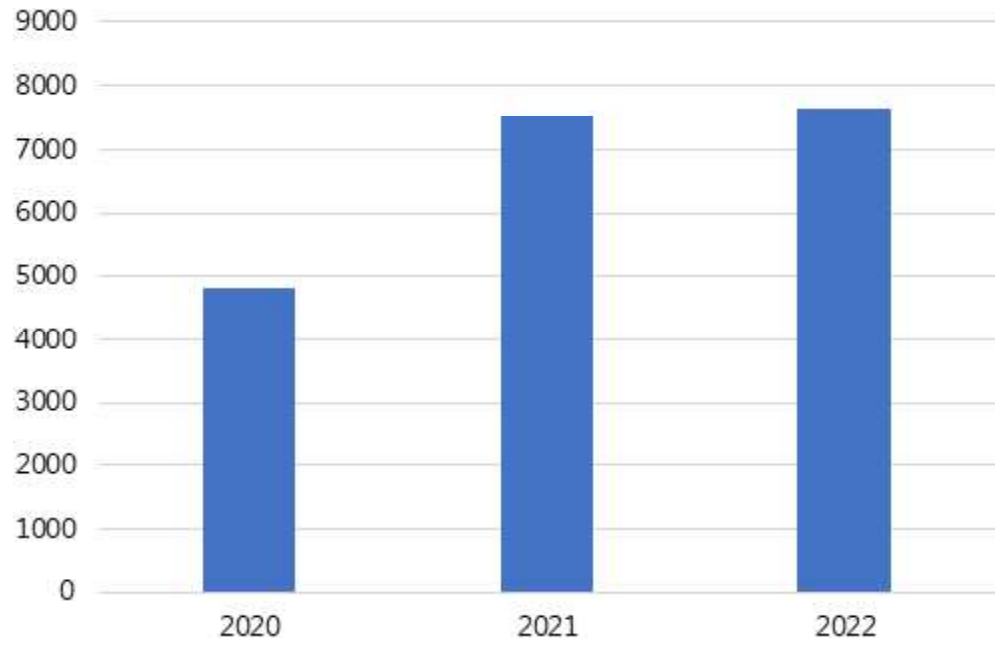
Table 46 : Descriptive Statistics and Test for Normal Probability Model

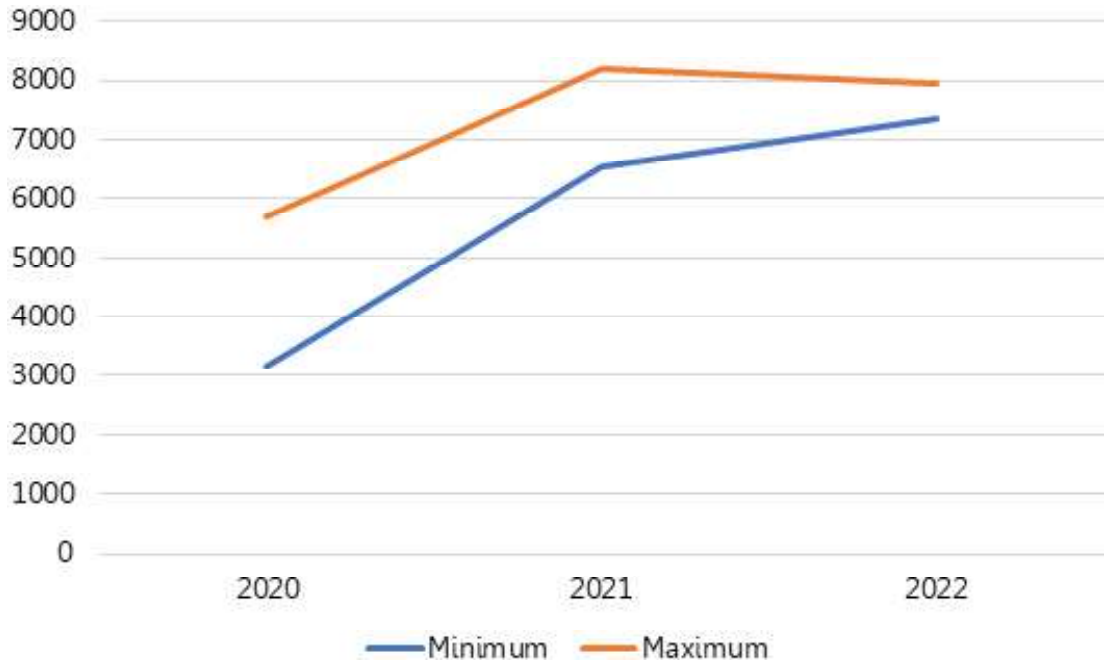
	2020	2021	2022
Valid	180	100	37
Missing	0	0	0
Mean	4808.815	7511.486	7655.139
Std. Deviation	584.551	411.23	158.859
Coefficient of Variation	0.122	0.055	0.021
Skewness	-1.078	-0.531	0.058
Std. Error of Skewness	0.181	0.241	0.388
Kurtosis	0.44	-0.261	-0.337
Std. Error of Kurtosis	0.36	0.478	0.759
Shapiro-Wilk	0.888	0.955	0.958
P-value of Shapiro-Wilk	< .001	0.002	0.17
Minimum	3158.58	6547.4	7340.55
Maximum	5704.83	8216.85	7949.6

Source: From researcher's data analysis



Graph 23 : Mean Values of the Index

Source: From researcher's data analysis

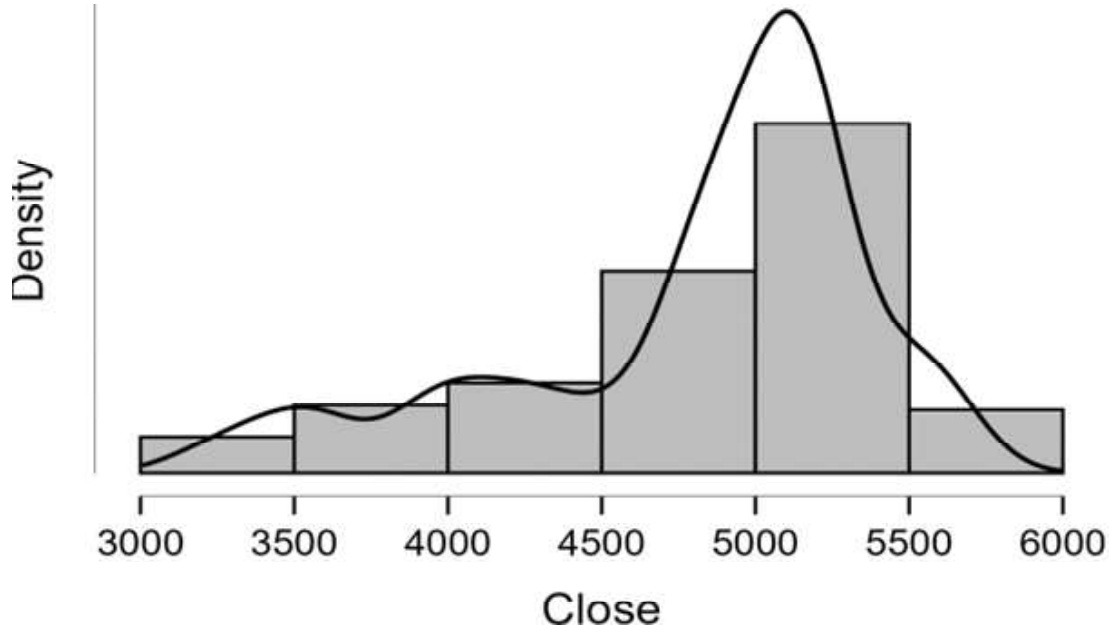


Graph 24 : Maximum and Minimum Values of the Index

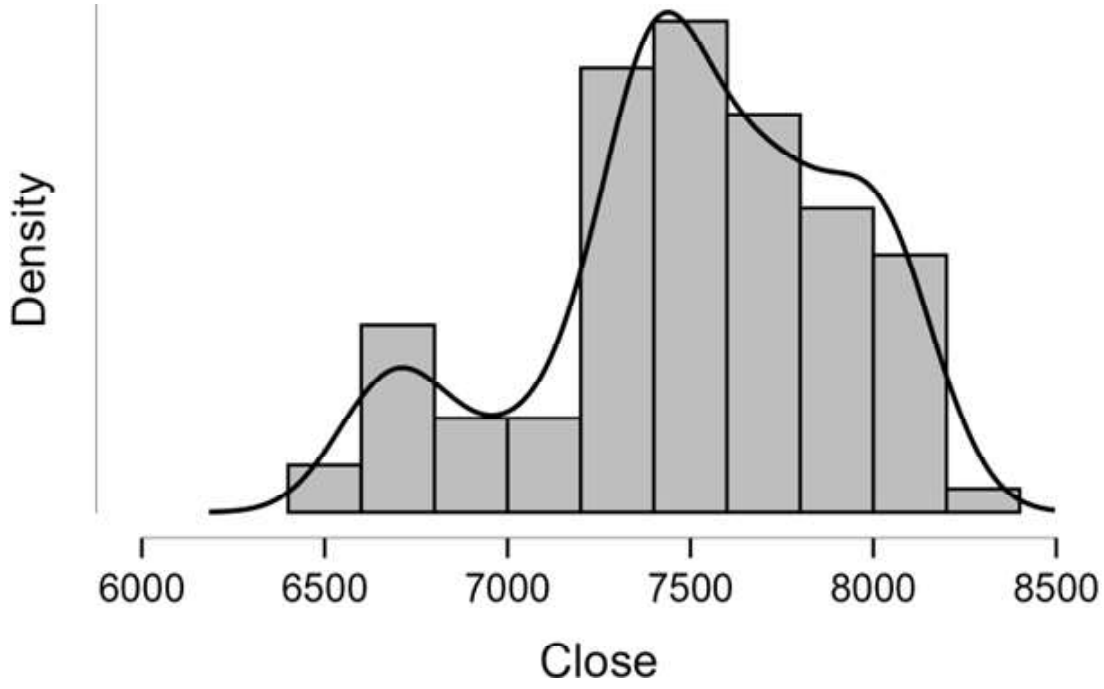
Source: From researcher's data analysis

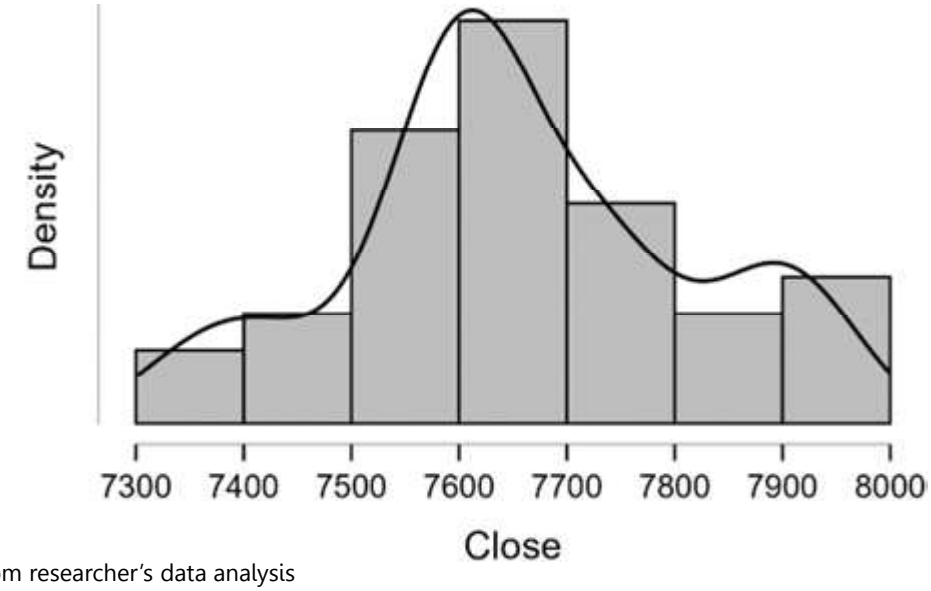
Distribution Plots

2020



2021





Source: From researcher's data analysis

Table 47 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2020	-0.5921	1.6890	Weibull	0.1058	9.4499	Fréchet
2021	-0.5328	1.8770	Weibull	-0.0939	10.6537	Weibull
2022	-0.3359	2.9772	Weibull	-0.3186	3.1390	Weibull

Source: From researcher's data analysis

Table 48 : Tail index and classification of the Index

	Shape	Scale	Comments based on values of index
2020	2.379103	3158.58	heavy-tailed and only mean exists
2021	7.124003	6547.4	heavy-tailed and moments of higher order exists
2022	22.18487	7340.55	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 49 : Index value for Stable Models

	α	β	σ	μ	Model
2020	1.17772	-1	218.689	4792.95	Stable
2021	1.98005	0	286.857	7504.74	Stable
2022	2	0	113.116	7655.48	Normal

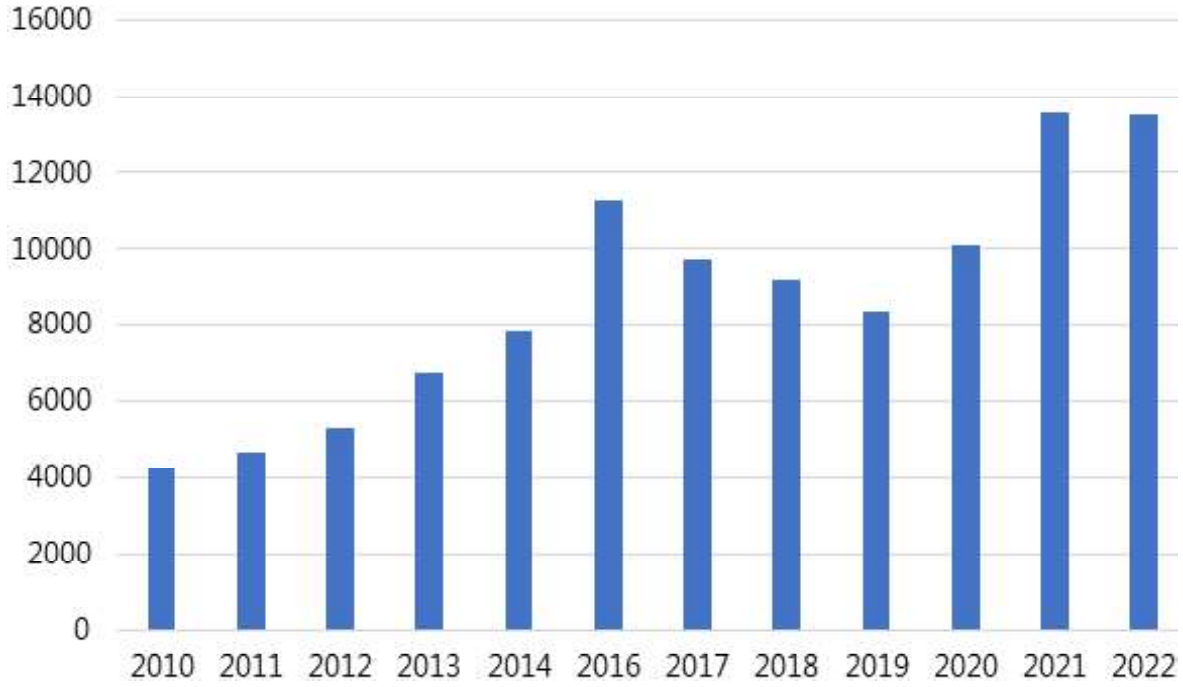
Source: From researcher's data analysis

NIFTY PHARMA

Table 50 : Descriptive Statistics and Test for Normal Probability Model

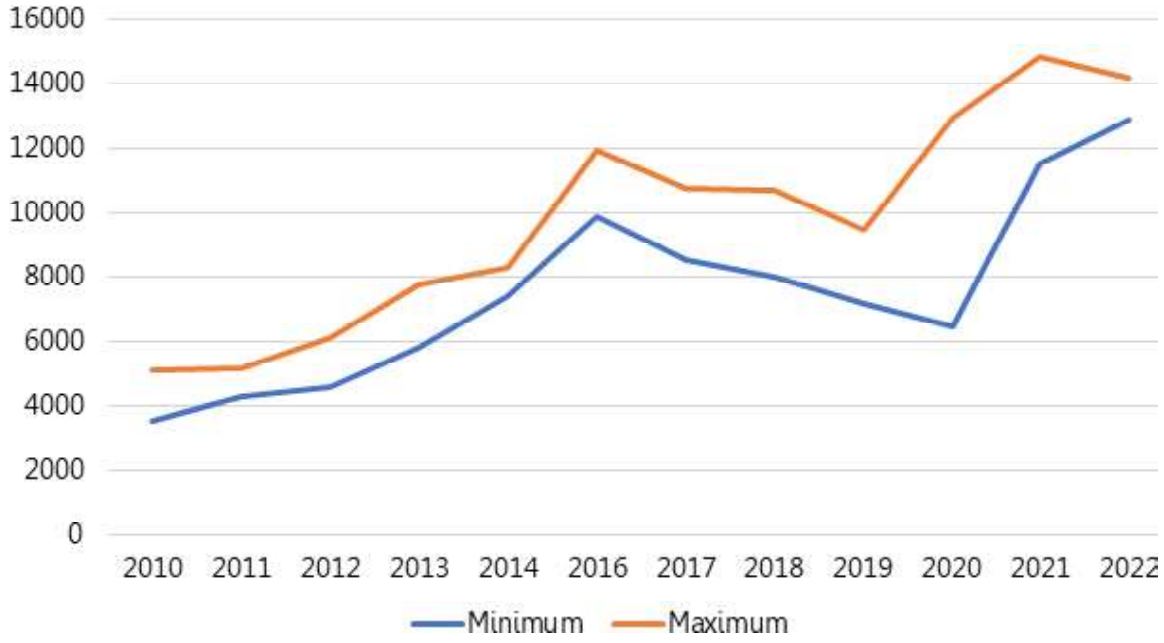
	2010	2011	2012	2013	2014	2016	2017	2018	2019	2020	2021	2022
Valid	252	247	251	250	108	114	248	246	245	252	247	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean	4241.527	4634.364	5277.226	6768.584	7809.242	11271.99	9747.184	9185.86	8365.761	10097.94	13608.42	13511.86
Std. Deviation	445.952	166.992	388.123	595.289	179.051	479.769	589.554	566.721	576.123	1692.395	810.137	361.618
Coefficient of Variation	0.105	0.036	0.074	0.088	0.023	0.043	0.06	0.062	0.069	0.168	0.06	0.027
Skewness	0.48	0.706	0.243	-0.162	-0.035	-0.964	-0.027	0.39	0.301	-0.277	-0.697	-0.088
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.233	0.226	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-0.839	0.303	-1.159	-1.347	-0.223	0.053	-1.191	-0.246	-1.043	-1.085	-0.575	-1.024
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.461	0.449	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.922	0.958	0.945	0.921	0.988	0.896	0.948	0.983	0.94	0.944	0.924	0.965
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	0.483	< .001	< .001	0.005	< .001	< .001	< .001	0.29
Minimum	3481.7	4300.2	4567.6	5778.2	7411.6	9889.3	8490.2	7983.2	7148.95	6432.3	11514.45	12847.9
Maximum	5085.3	5172.9	6084.6	7731.5	8276.5	11936	10731	10661.25	9461.7	12915.9	14812.4	14156.4

Source: From researcher's data analysis



Graph 25 : Mean values of the Index

Source: From researcher's data analysis

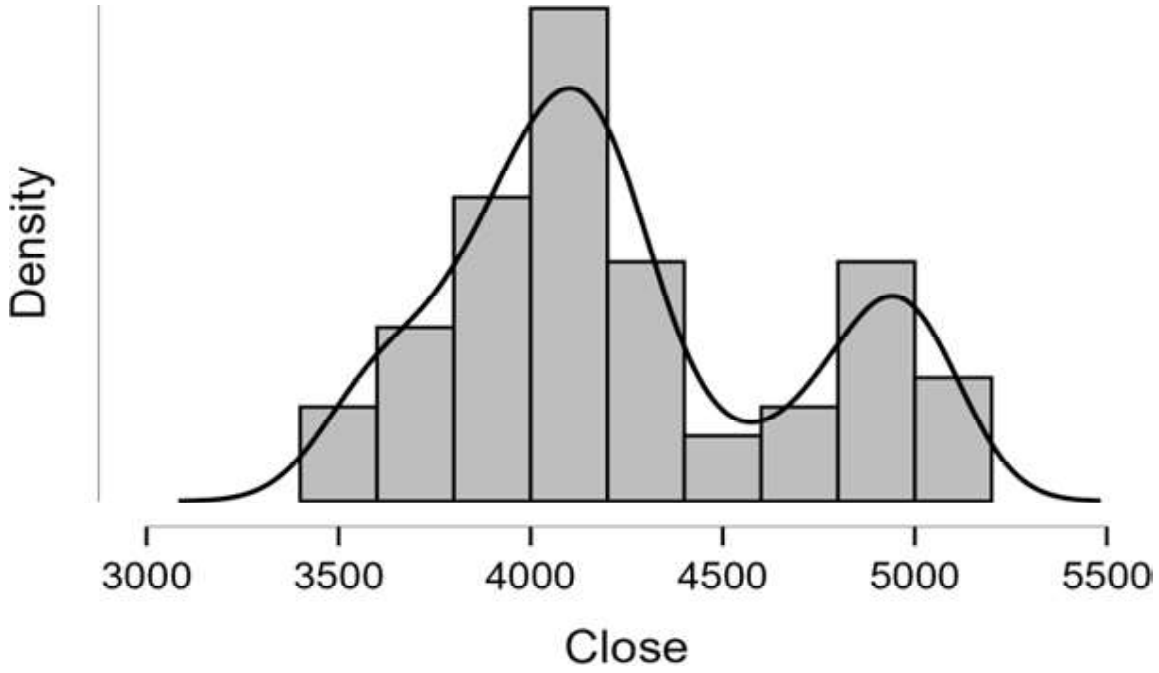


Graph 26 : Maximum and Minimum values of the Index

Source: From researcher's data analysis

Distribution Plots

2010



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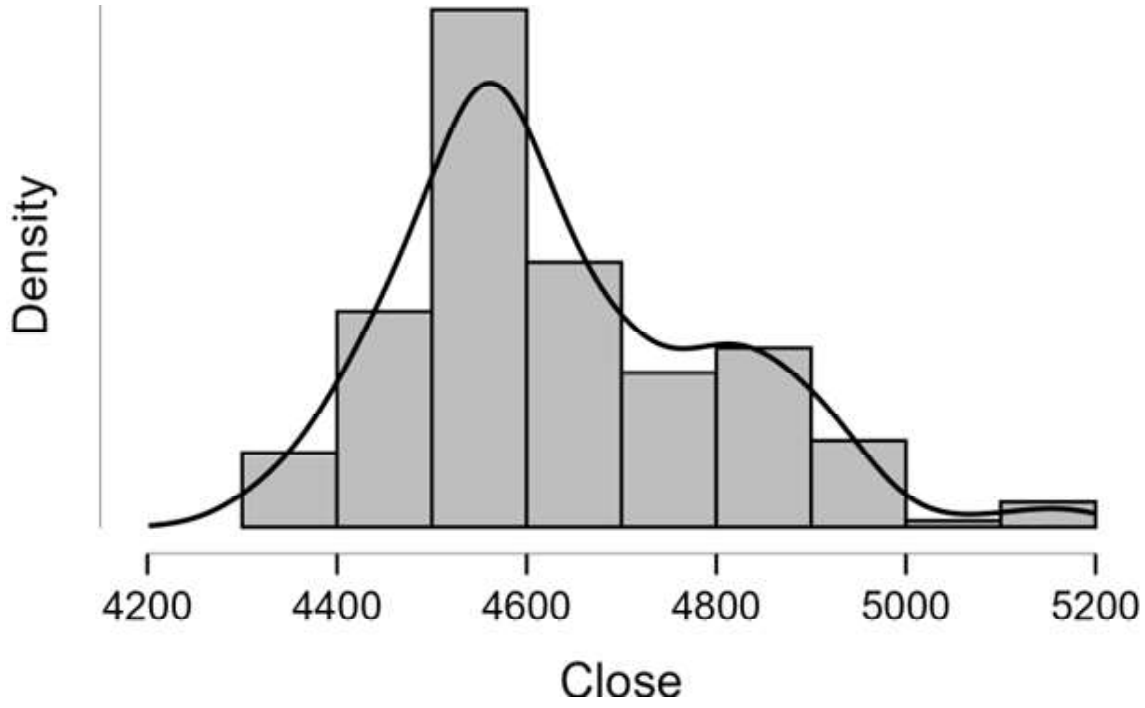

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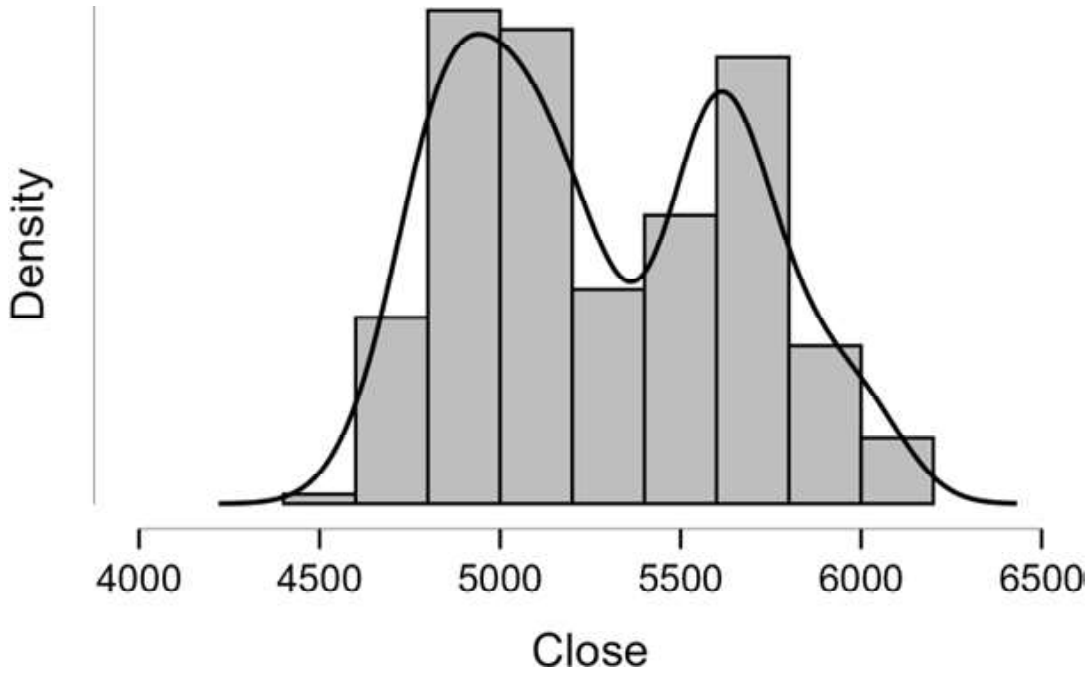
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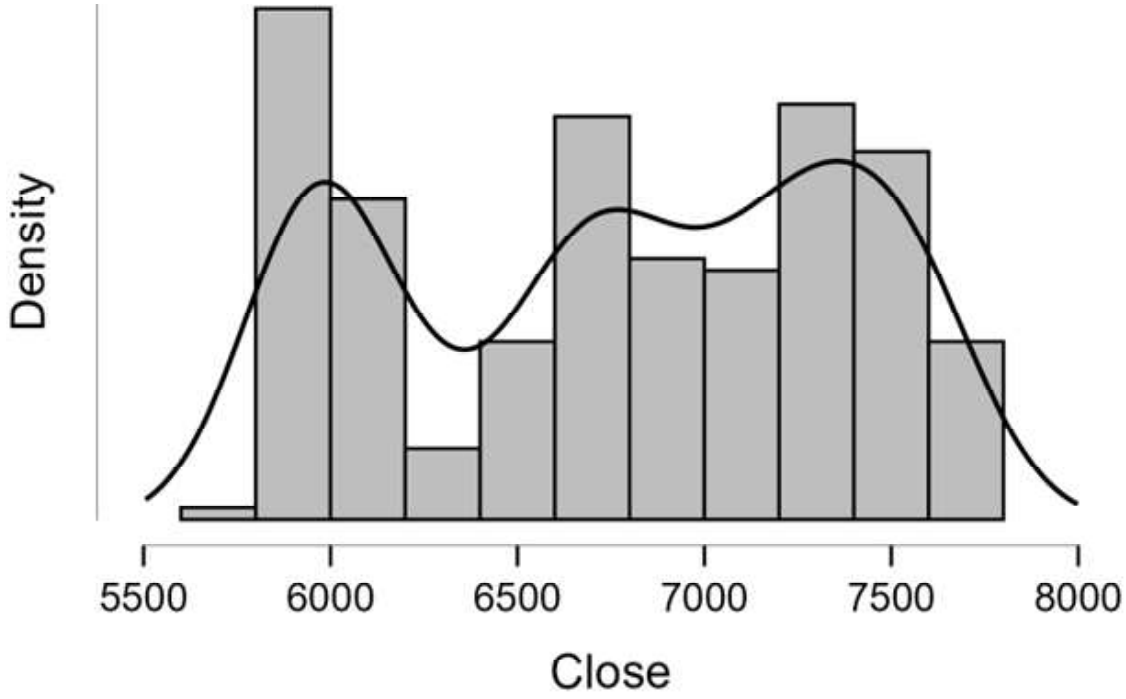
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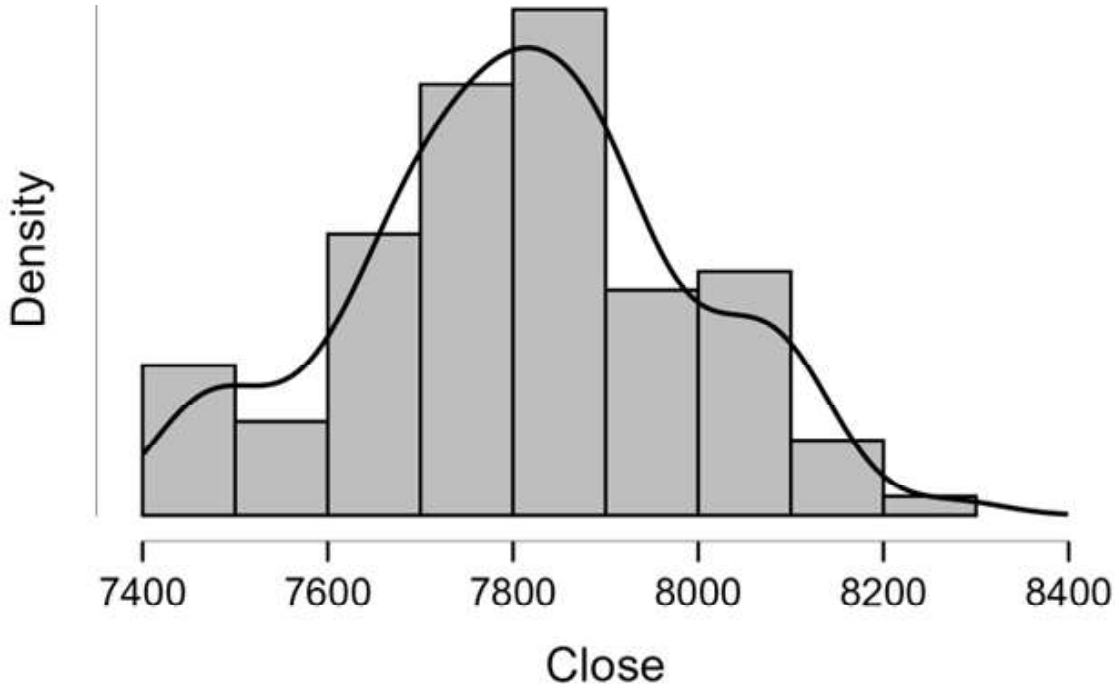
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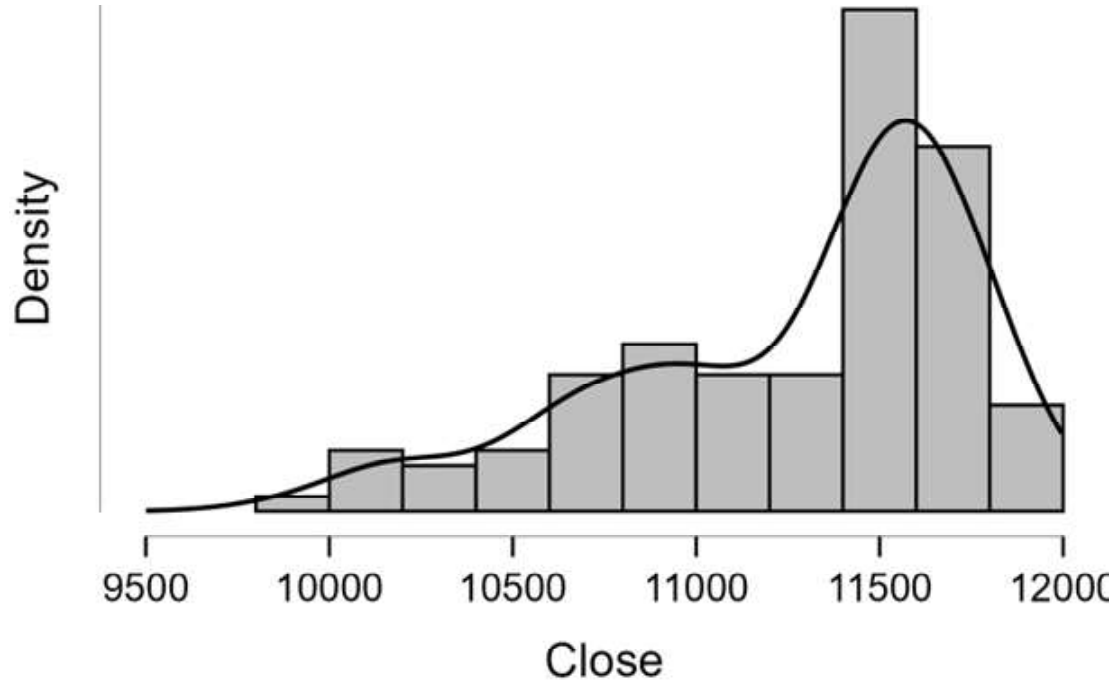
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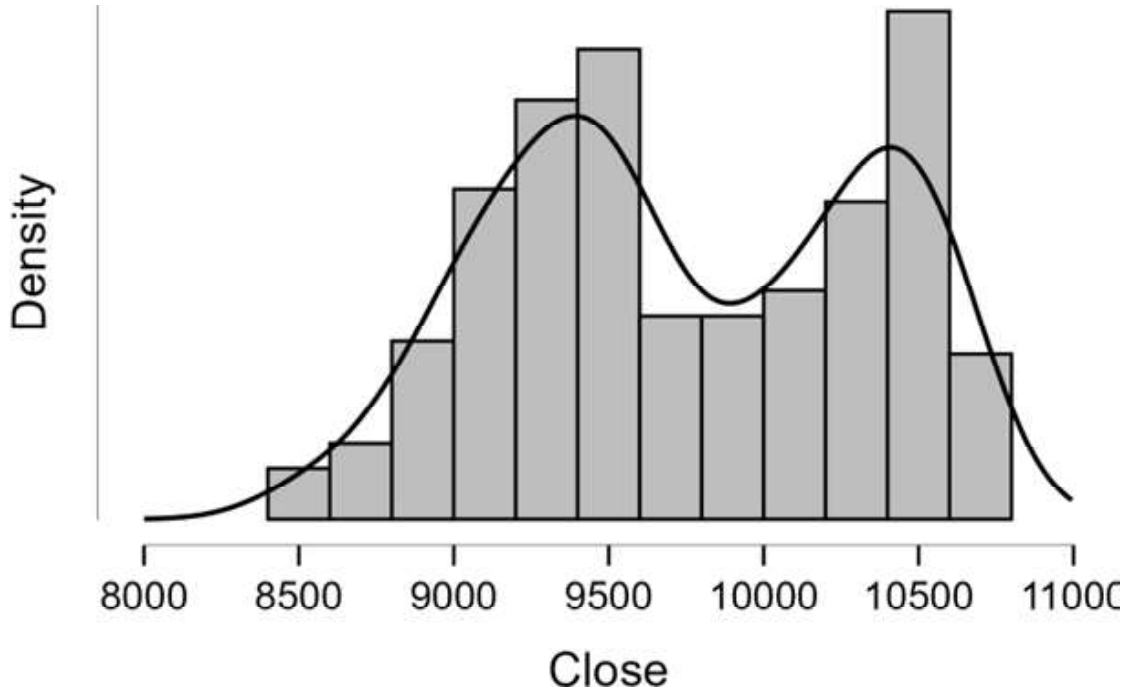
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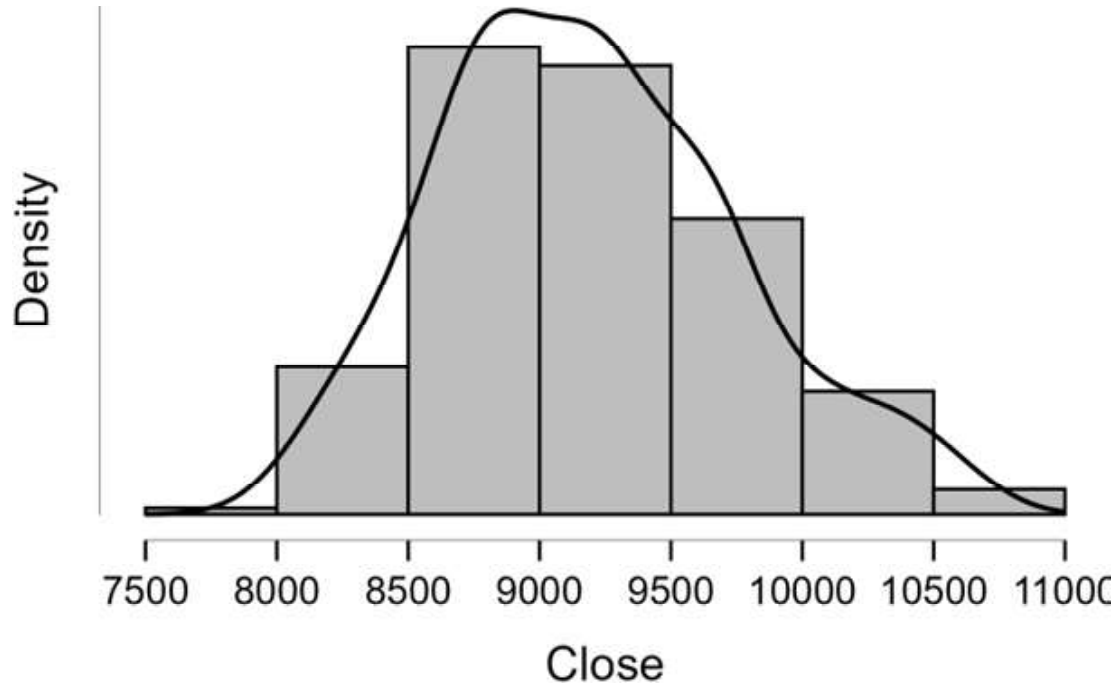
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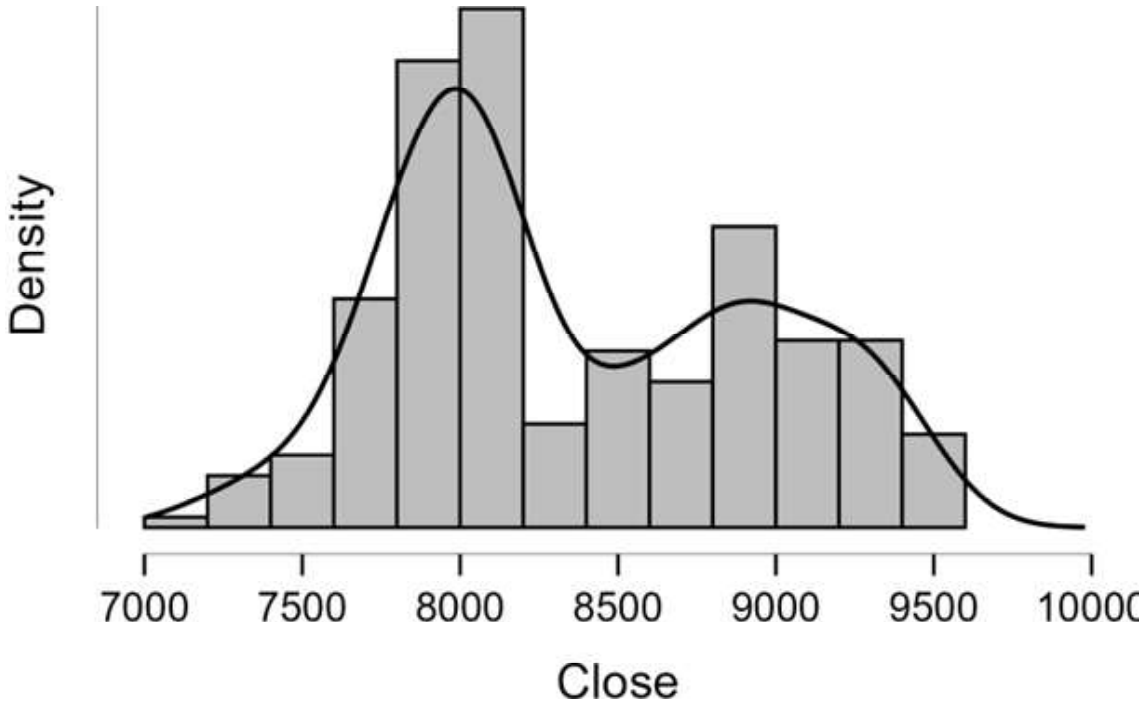
2019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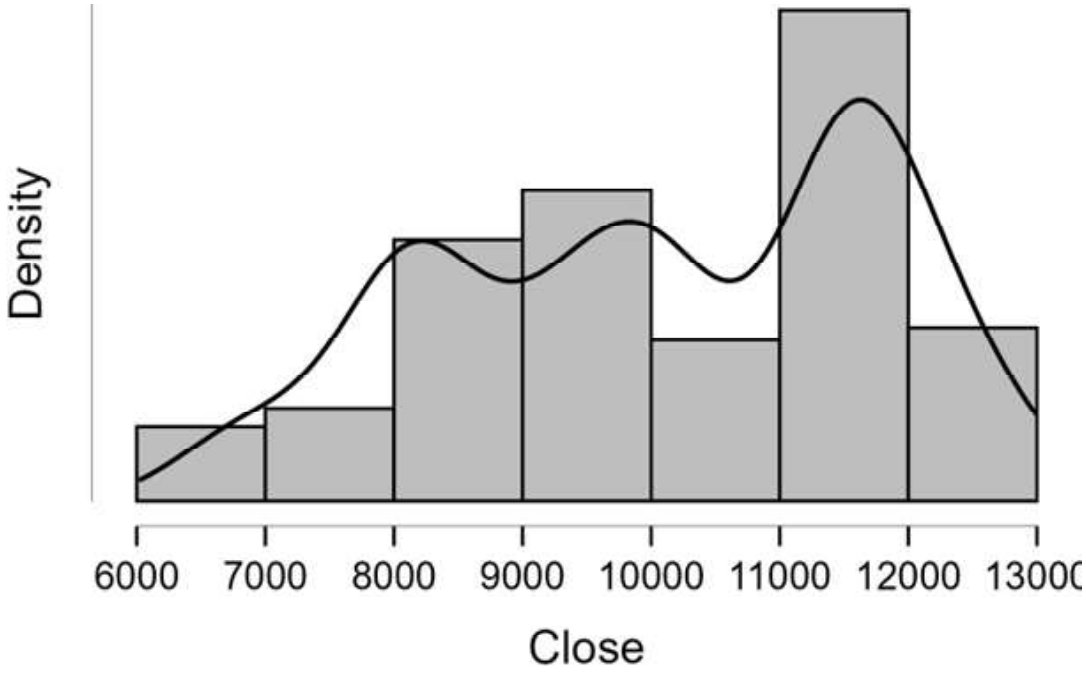
2020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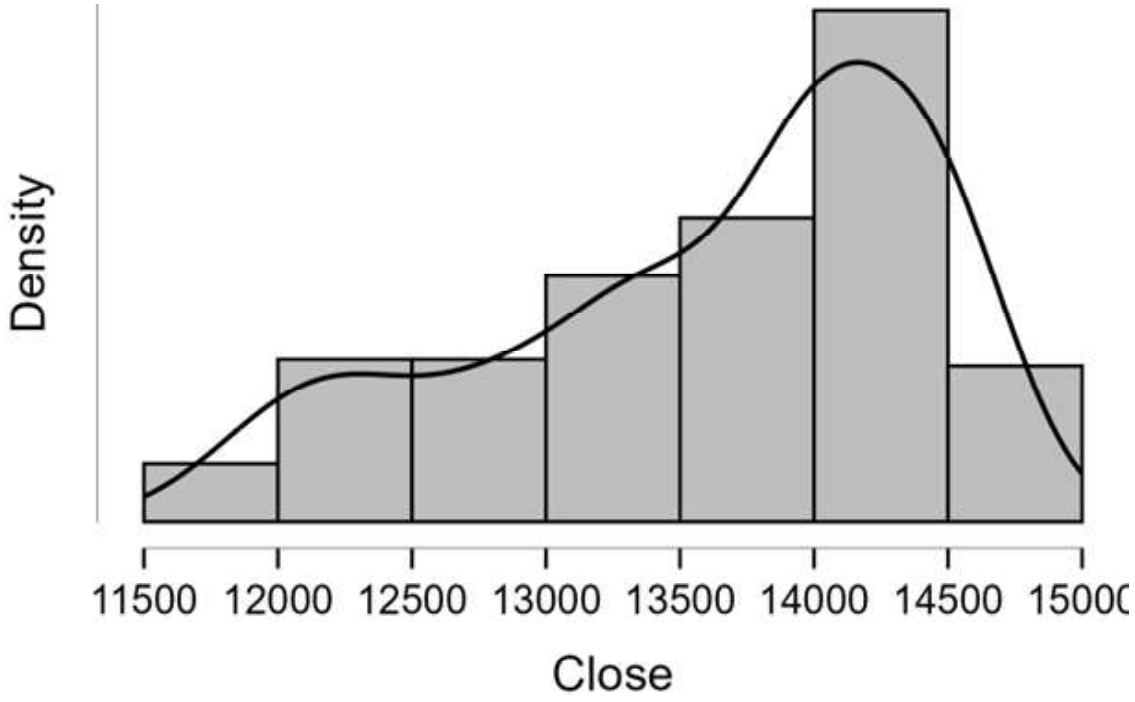
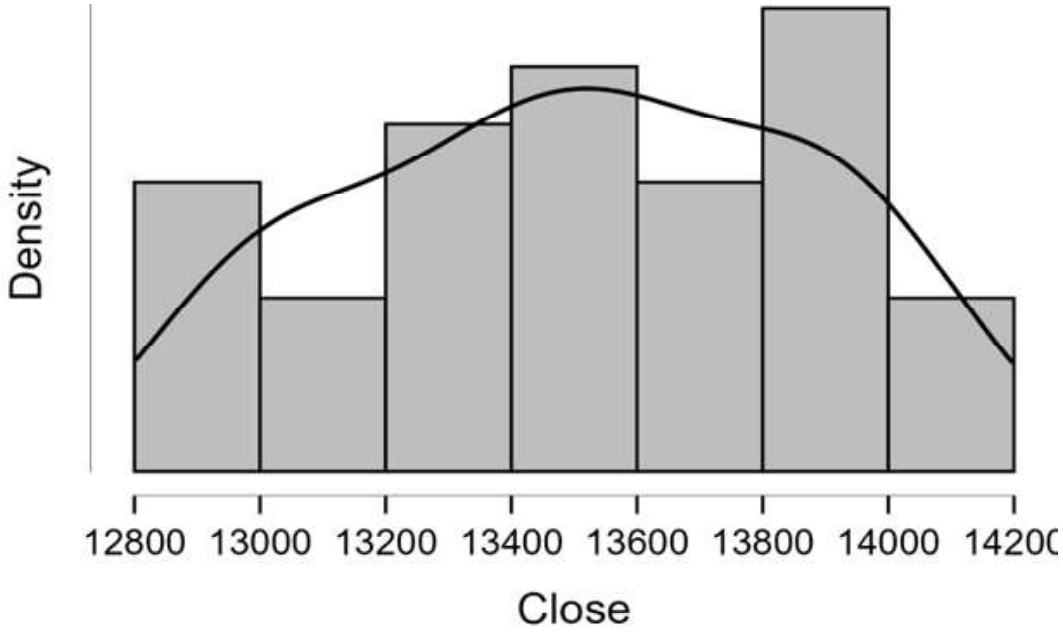
2021



2022



Source: From researcher's data analysis

Table 51 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.0686	14.5800	Weibull	-0.5456	1.8329	Weibull
2011	-0.0611	16.3778	Weibull	-0.4530	2.2075	Weibull
2012	-0.1912	5.2290	Weibull	-0.3919	2.5519	Weibull
2013	-0.6014	1.6628	Weibull	-0.3710	2.6951	Weibull
2014	-0.2629	3.8039	Weibull	-0.2897	3.4516	Weibull
2016	-0.6417	1.5585	Weibull	0.2284	4.3782	Fréchet
2017	-0.3380	2.9584	Weibull	-0.3305	3.0256	Weibull
2018	-0.1625	6.1557	Weibull	-0.3996	2.5025	Weibull
2019	-0.1748	5.7225	Weibull	-0.4200	2.3812	Weibull
2020	-0.5164	1.9366	Weibull	-0.1653	6.0482	Weibull
2021	-0.6321	1.5821	Weibull	0.1523	6.5647	Fréchet
2022	-0.4264	2.3450	Weibull	-0.3333	3.0003	Weibull

Source: From researcher's data analysis

Table 52 : Tail index and classification of the Index

	Shape	Scale	Comments based on the Index values
2010	5.131017	3481.7	heavy-tailed and moments of higher order exists
2011	13.26808	4300.2	heavy-tailed and moments of higher order exists
2012	6.95026	4567.6	heavy-tailed and moments of higher order exists
2013	6.385585	5778.2	heavy-tailed and moments of higher order exists
2014	18.64604	7411.6	heavy-tailed and moments of higher order exists
2016	7.470141	9889.3	heavy-tailed and moments of higher order exists
2017	7.215513	8490.2	heavy-tailed and moments of higher order exists
2018	7.114943	7983.2	heavy-tailed and moments of higher order exists
2019	6.361356	7148.95	heavy-tailed and moments of higher order exists
2020	2.259274	6432.3	heavy-tailed and only mean exists
2021	5.960913	11514.45	heavy-tailed and moments of higher order exists
2022	18.51207	12847.9	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 53 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	324.825	4247.7323	Normal
2011	1.92837	1	112.691	4625.459419	Stable
2012	2.0000	0.0000	297.7031	5279.5566	Normal
2013	2	0	462.084	6766.134	Normal
2014	2	0	127.439	7809.0359	Normal
2015					Stable
2016	1.7277	-1.0000	293.6726	11372.9019	Stable
2017	2	0	457.084	9746.9875	Normal
2018	2	0	402.036	9191.8092	Normal
2019	2	0	435.562	8370.4433	Normal
2020	2	0	1290.04	10086.3	Normal
2021	1.97974	-1	568.807	13609.19728	Stable
2022	2	0	272.203	13511.0817	Normal

Source: From researcher's data analysis

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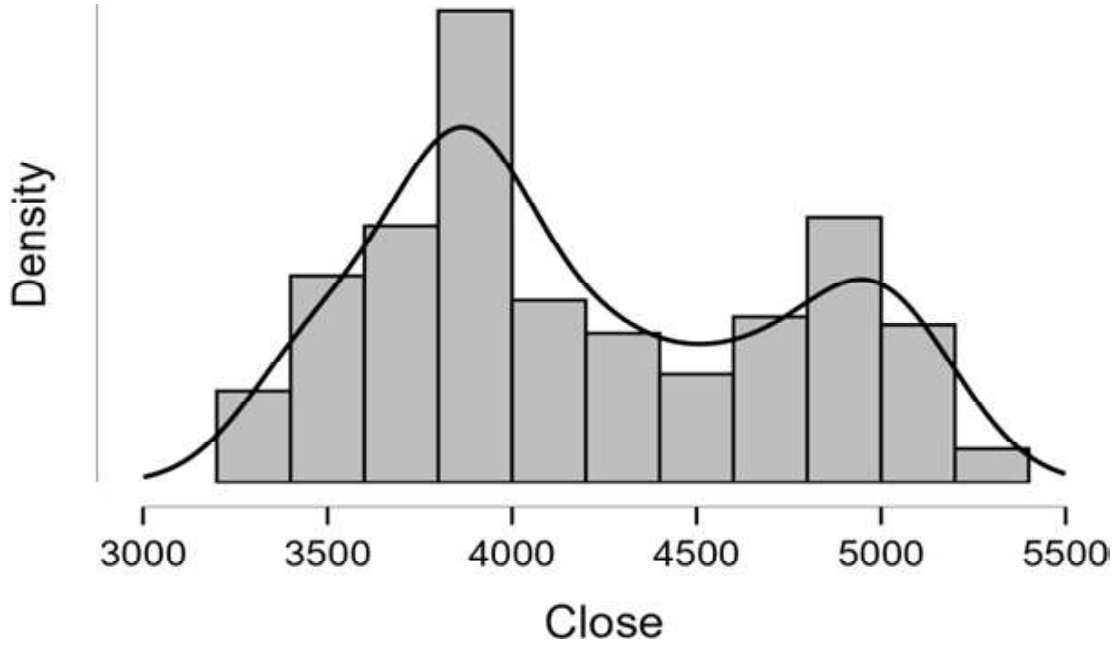
Table 54 : Descriptive Statistics and Test for Normal Probability Model

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	246	245	252	246	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	4196.596	4364.607	4858.136	5649.333	7375.578	9798.471	9853.041	12814.21	14767.56	16420.77	13495.49	18592.78	19193.85
Std. Deviation	544.751	312.286	510.155	472.944	1290.54	450.857	960.343	1162.261	610.589	849.143	2560.481	941.978	309.503
Coefficient of Variation	0.13	0.072	0.105	0.084	0.175	0.046	0.097	0.091	0.041	0.052	0.19	0.051	0.016
Skewness	0.352	-0.395	0.375	-0.71	-0.09	-0.106	-0.425	-0.723	0.099	-0.062	0.312	0.392	-0.037
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-1.139	-0.328	-0.054	0.217	-0.947	-0.68	-0.925	-0.657	-0.718	-1.373	-1.337	0.212	-0.322
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.932	0.974	0.955	0.962	0.949	0.984	0.947	0.897	0.977	0.932	0.901	0.986	0.979
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	0.008	< .001	< .001	< .001	< .001	< .001	0.016	0.712
Minimum	3311.8	3526.8	3549.3	4242.3	5147.4	8588.2	7632.4	9912.9	13418.35	14824.9	8974.3	16481.95	18531.85
Maximum	5245.5	4904.4	5967.8	6548.9	9673.2	10838	11501	14219	16088.9	17888.4	17913.65	21404.25	19857.15

Source: From researcher's data analysis

Distribution Plots

2010



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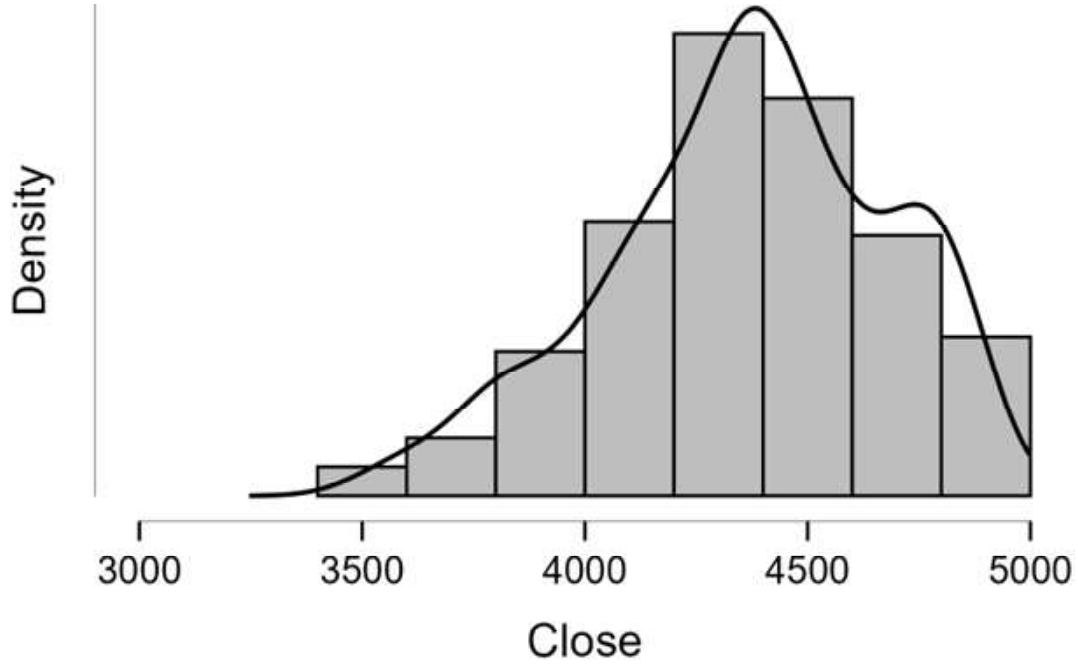

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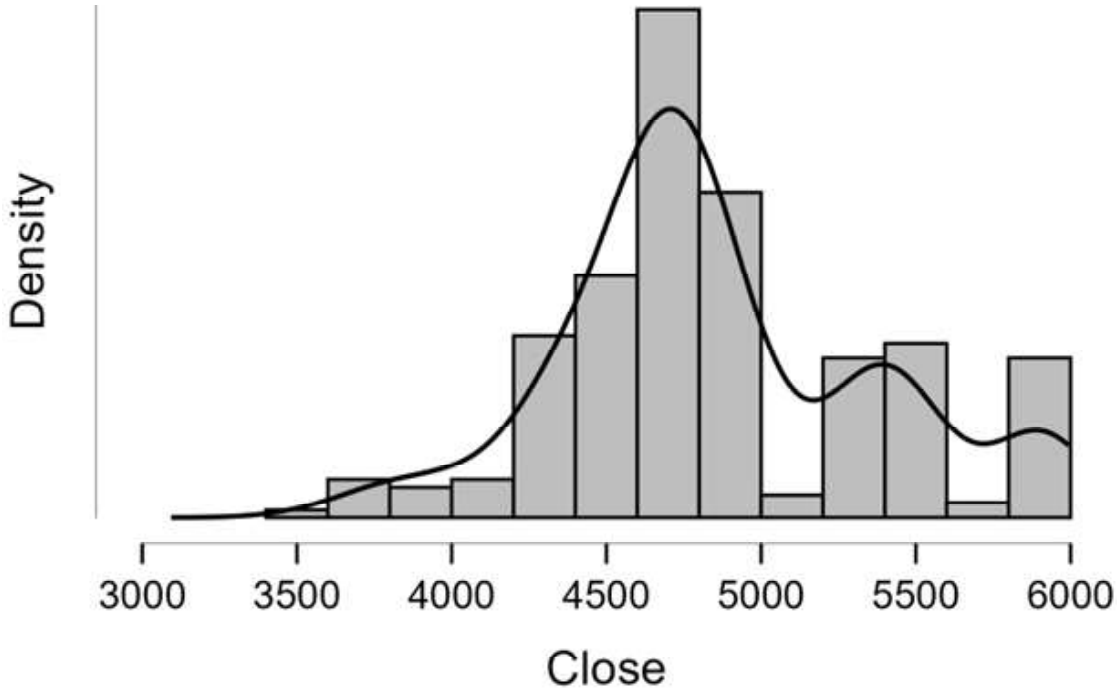
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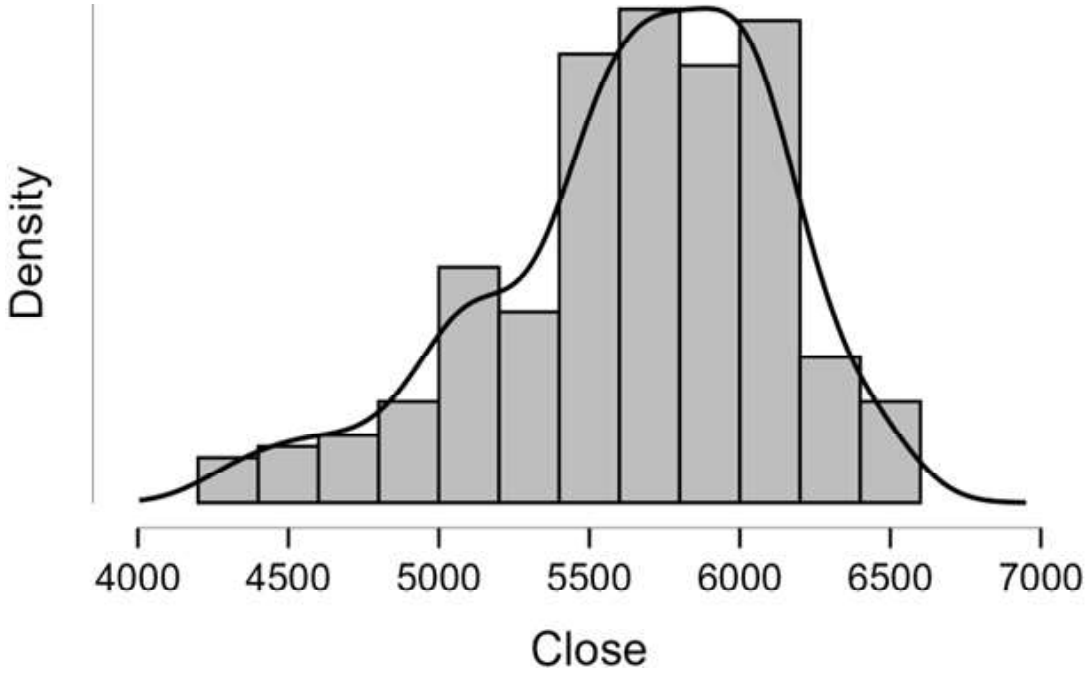
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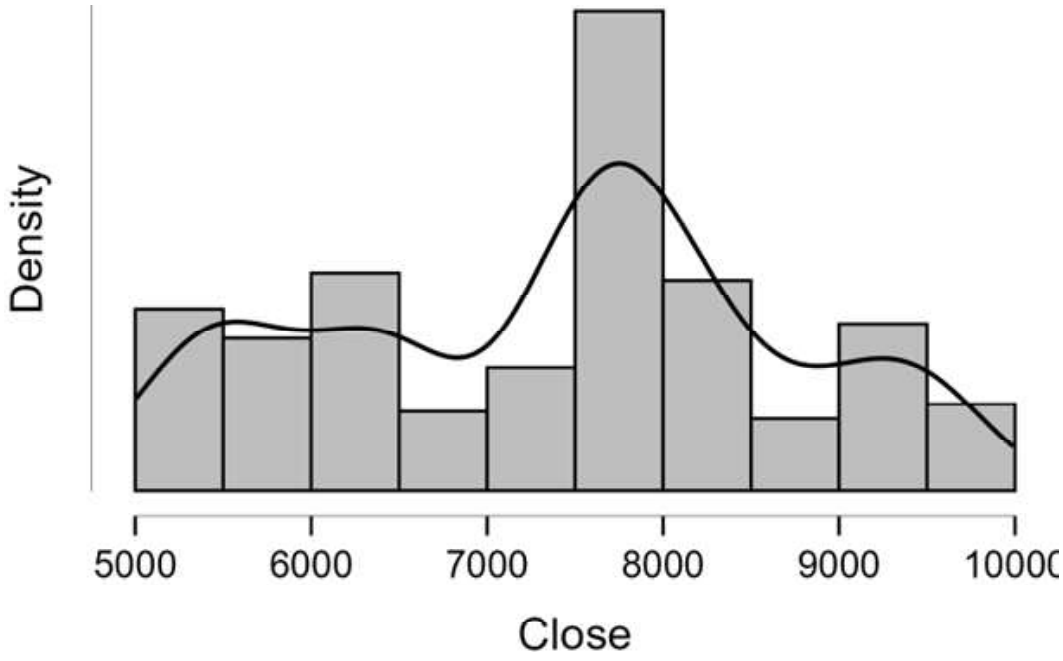
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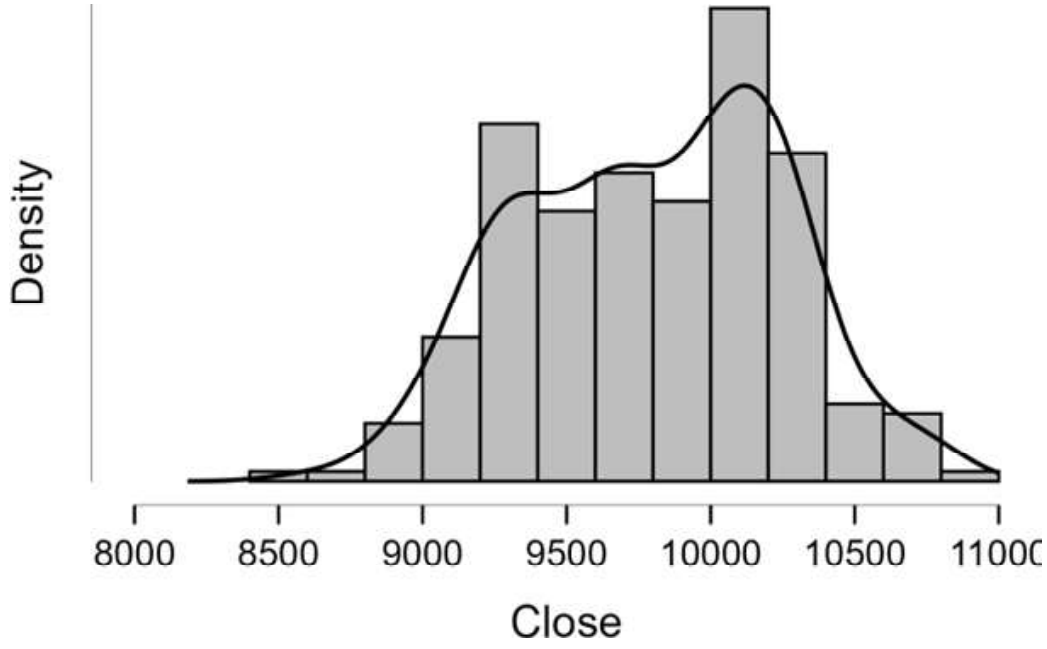
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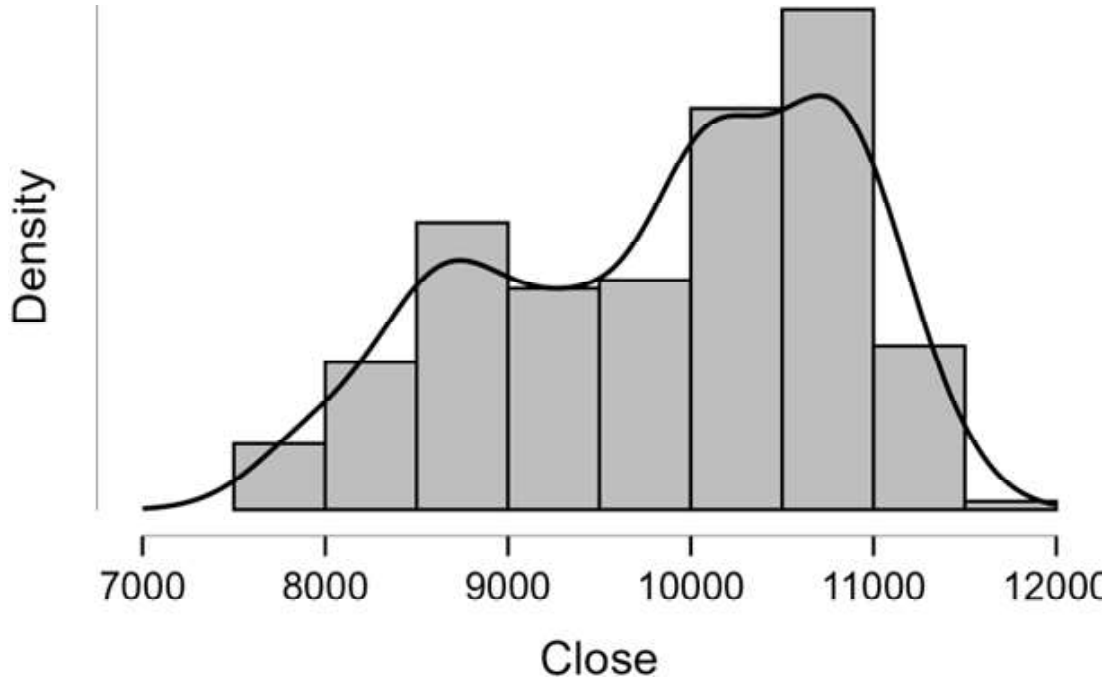
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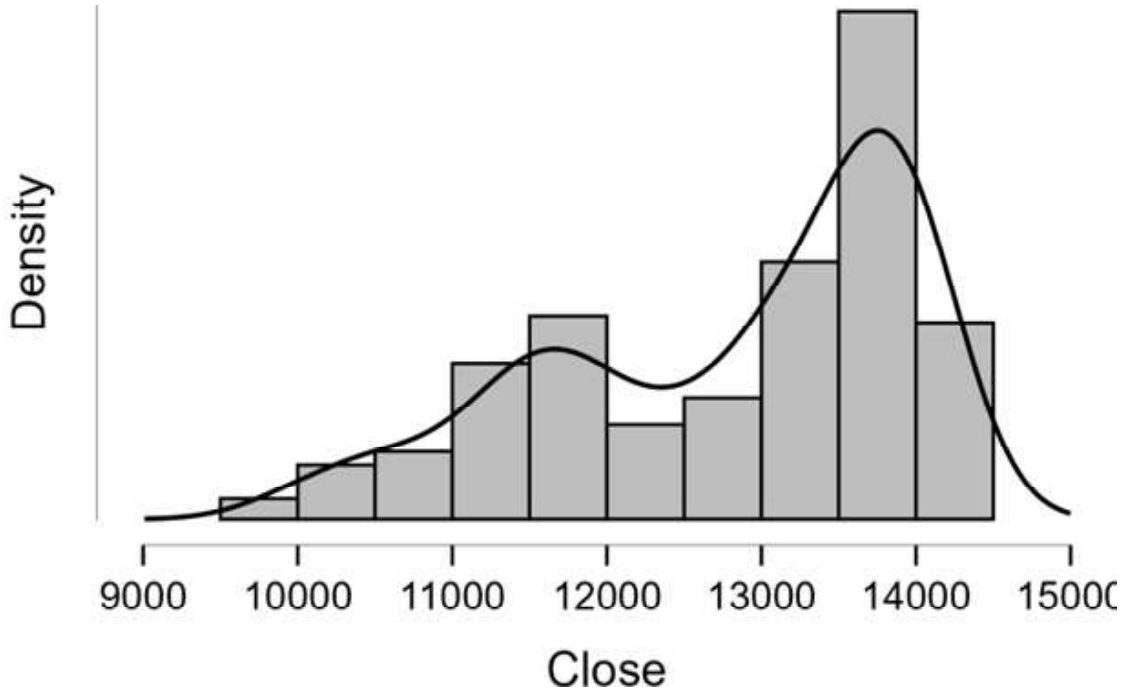
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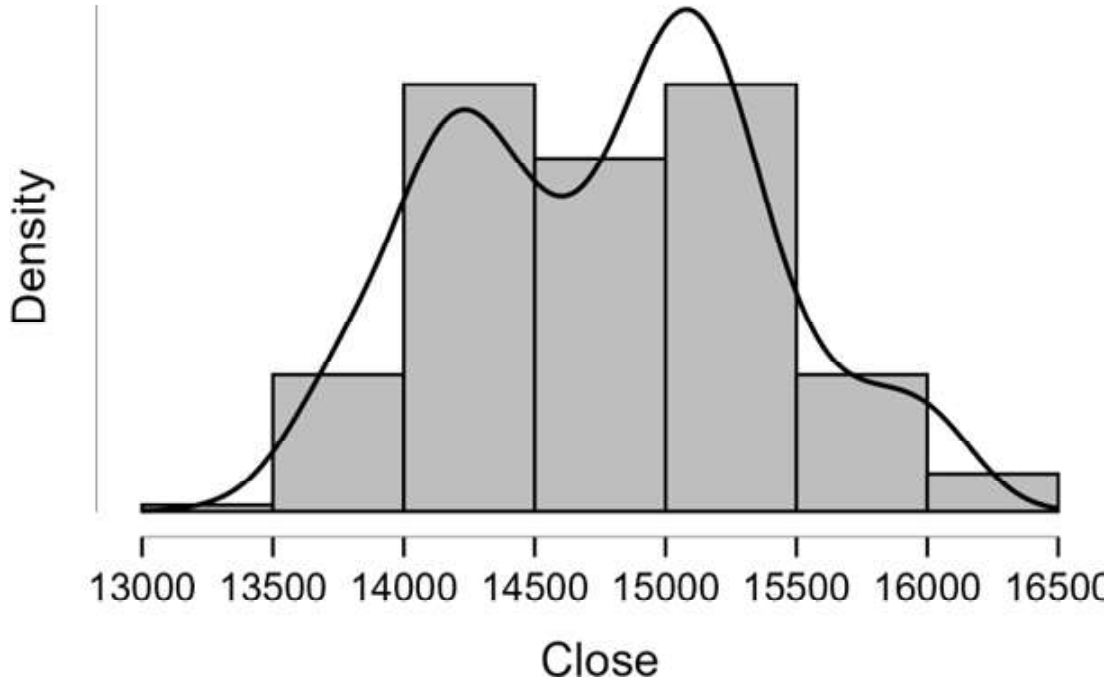
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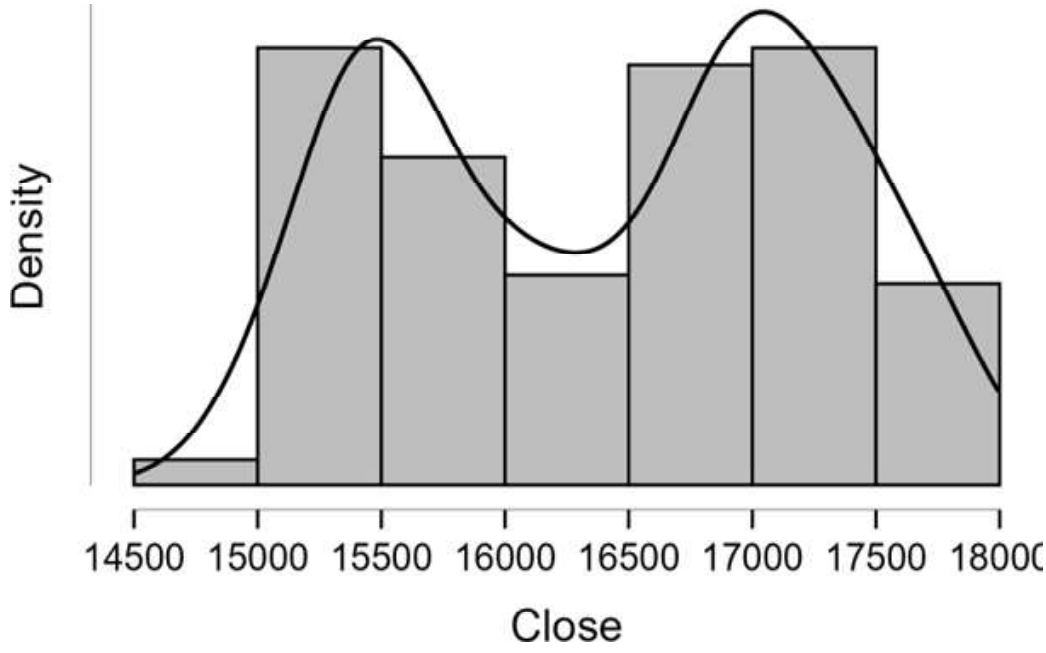
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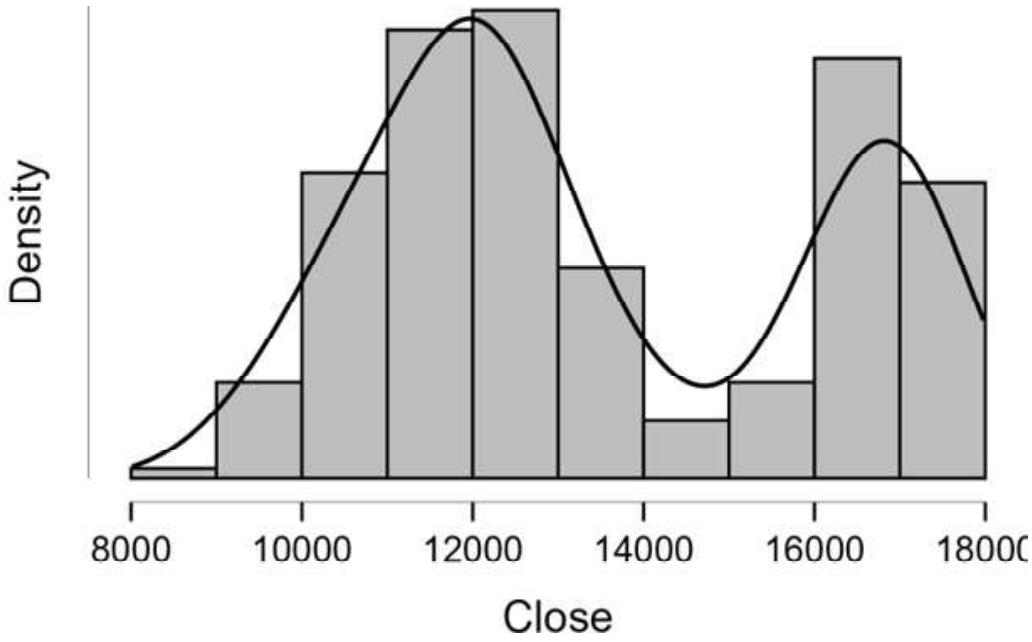
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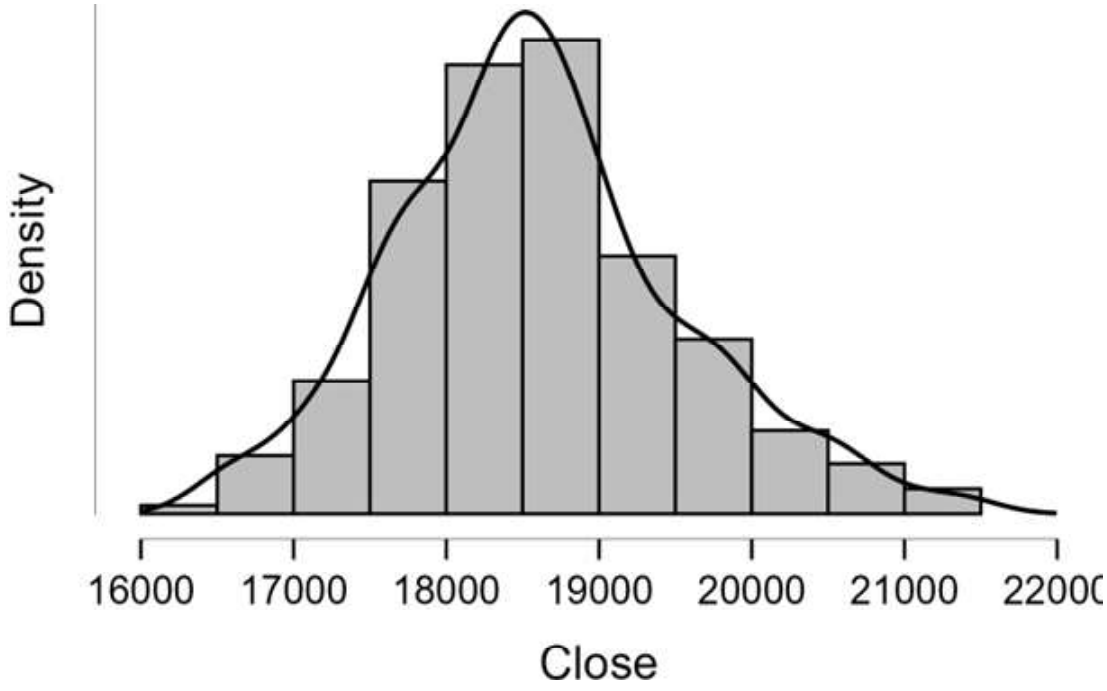
2021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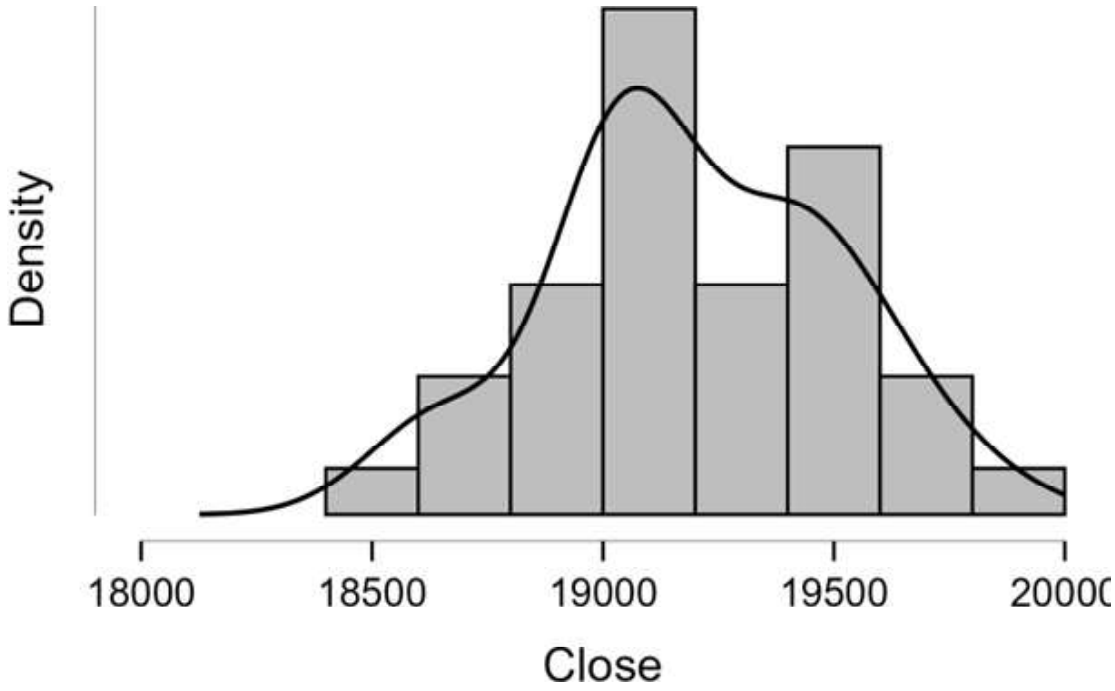

Source: From researcher's data analysis

Table 55 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.0935	10.6968	Weibull	-0.5762	1.7355	Weibull
2011	-0.6154	1.6249	Weibull	-0.1488	6.7206	Weibull
2012	-0.1950	5.1295	Weibull	-0.3582	2.7917	Weibull
2013	-0.4612	2.1682	Weibull	-0.0579	17.2627	Weibull
2014	-0.4080	2.4510	Weibull	-0.3431	2.9150	Weibull
2015	-0.3199	3.1260	Weibull	-0.2606	3.8374	Weibull
2016	-0.5463	1.8305	Weibull	-0.0417	23.9621	Weibull
2017	-0.7608	1.3145	Weibull	0.4179	2.3928	Fréchet
2018	-0.2708	3.6925	Weibull	-0.3678	2.7190	Weibull
2019	-0.4881	2.0488	Weibull	-0.4374	2.2864	Weibull
2020	-0.0748	13.3703	Weibull	-0.4893	2.0437	Weibull
2021	-0.1742	5.7413	Weibull	-0.3641	2.7464	Weibull
2022	-0.3124	3.2007	Weibull	-0.2865	3.4900	Weibull

Source: From researcher's data analysis

Table 56 : Tail index and classification of the Index

	Shape	Scale	Comments based on the values of Index
2010	4.311166	3311.8	heavy-tailed and moments of higher order exists
2011	4.679131	3526.8	heavy-tailed and moments of higher order exists
2012	3.194264	3549.3	heavy-tailed and moments of higher order exists
2013	3.483845	4242.3	heavy-tailed and moments of higher order exists
2014	2.865161	5147.4	heavy-tailed and only mean exists
2015	7.516402	8588.2	heavy-tailed and moments of higher order exists
2016	3.931015	7632.4	heavy-tailed and moments of higher order exists
2017	3.900578	9912.9	heavy-tailed and moments of higher order exists
2018	10.37321	13418.35	heavy-tailed and moments of higher order exists
2019	9.758685	14824.9	heavy-tailed and moments of higher order exists
2020	2.525052	8974.3	heavy-tailed and only mean exists
2021	8.26119	16481.95	heavy-tailed and moments of higher order exists
2022	26.48675	18531.85	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 57 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	413.1295	4201.68	Normal
2011	2	0	223.4745	4361.4258	Normal
2012	1.9250	1.0000	346.0073	4824.8455	Stable
2013	1.88495	-1	312.3933	5693.2844	Stable
2014	2	0	973.9354	7372.2586	Normal
2015	2	0	335.4837	9797.1996	Normal
2016	2.0000	0.0000	716.3112	9842.3041	Normal
2017	1.99812	0	825.1699	12789.856	Stable
2018	2	0	454.7552	14768.909	Normal
2019	2	0	662.3585	16419.393	Normal
2020	2	0	1972.98	13516.52	Normal
2021	1.93854	1	640.0427	18542.917	Stable
2022	2	0	222.0367	19193.635	Normal

Source: From researcher's data analysis

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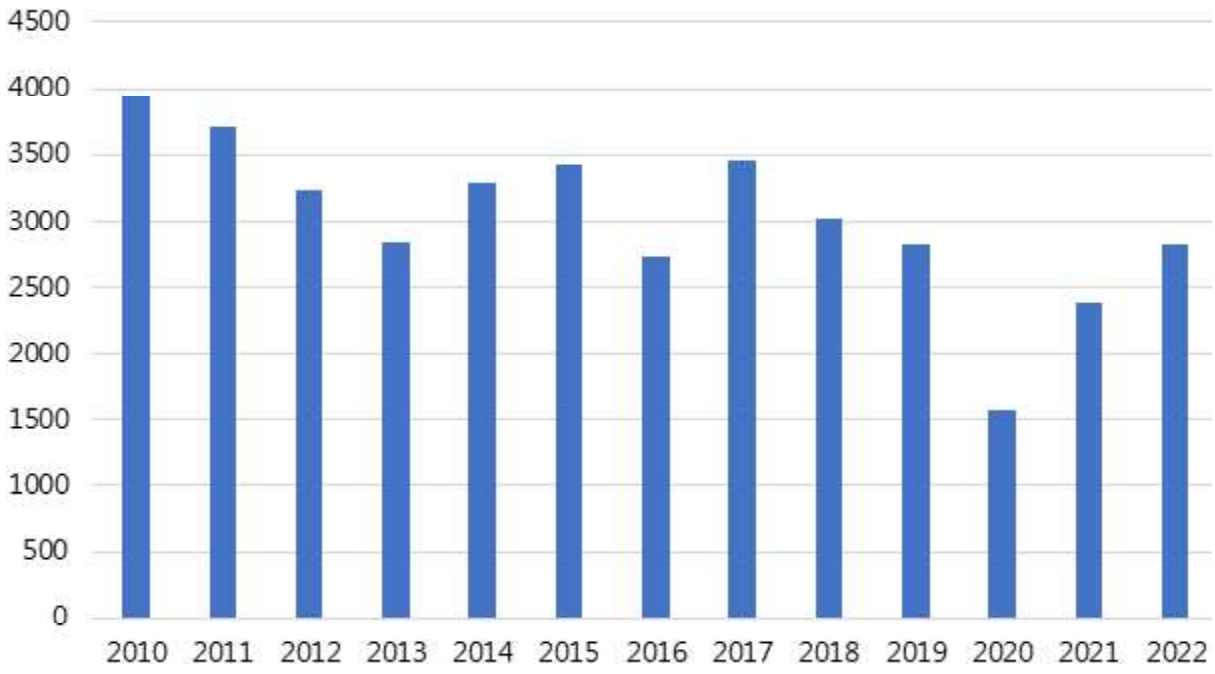
Table 58 : Descriptive Statistics and Test for Normal Probability Model

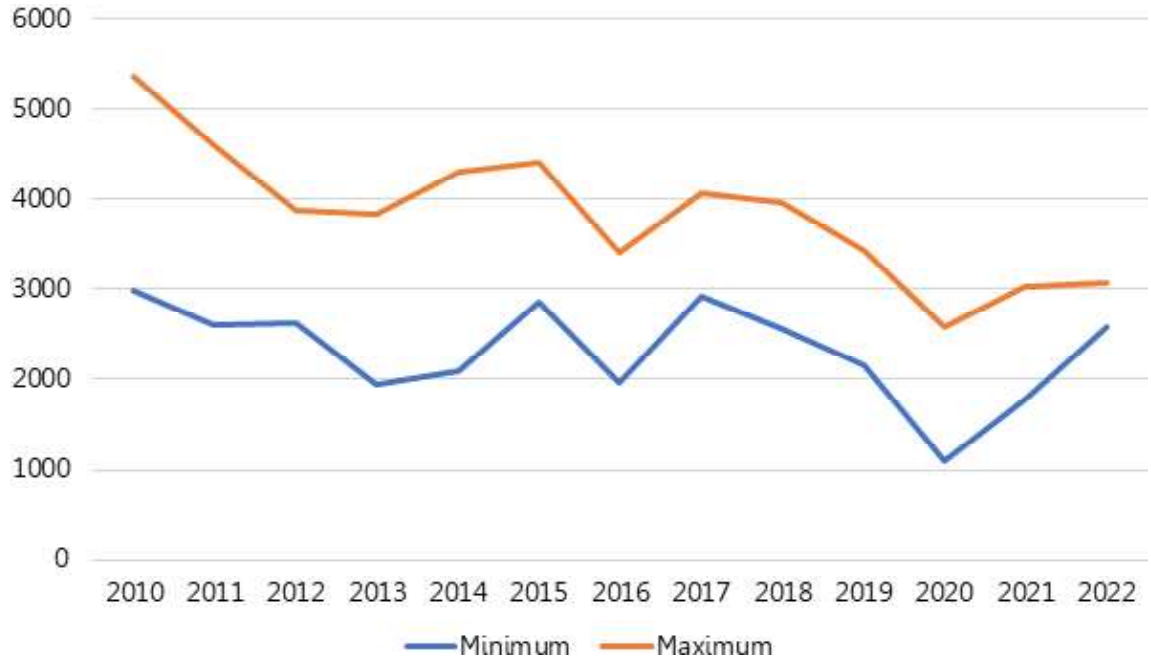
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	246	245	252	247	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	3943.665	3717.184	3228.949	2832.547	3285.895	3424.936	2729.461	3460.104	3025.592	2817.402	1573.965	2385.887	2831.641
Std. Deviation	675.638	525.876	269.601	531.191	661.497	367.472	392.024	280.952	281.546	340.234	380.264	268.72	133.609
Coefficient of Variation	0.171	0.141	0.083	0.188	0.201	0.107	0.144	0.081	0.093	0.121	0.242	0.113	0.047
Skewness	0.413	-0.311	-0.259	0.221	-0.456	0.809	-0.147	0.202	1.163	-0.18	1.256	-0.094	0.228
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-1.197	-1.09	-0.643	-1.146	-1.094	0.153	-1.329	-0.682	0.779	-1.212	0.394	-0.108	-0.916
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.916	0.943	0.974	0.946	0.91	0.939	0.933	0.975	0.891	0.946	0.818	0.98	0.946
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	0.002	0.074
Minimum	2983.3	2602.9	2619.4	1939	2086.4	2864.3	1968	2916.1	2572.85	2150.35	1087.2	1783.85	2584.7
Maximum	5375.8	4612.2	3887.2	3836.1	4309.3	4419.2	3411.6	4068.8	3965.6	3425.1	2576.7	3040.6	3066.1

Source: From researcher's data analysis



Graph 27 : Mean values of the index

Source: From researcher's data analysis

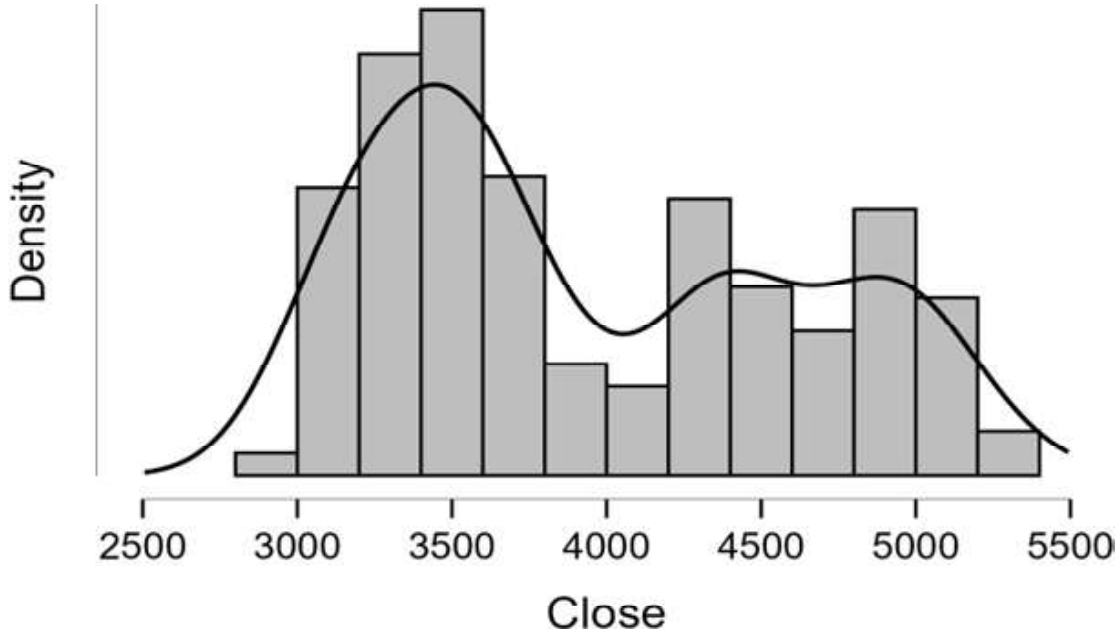


Graph 28 : Maximum and Minimum values of the index

Source: From researcher's data analysis

Distribution Plots

2010



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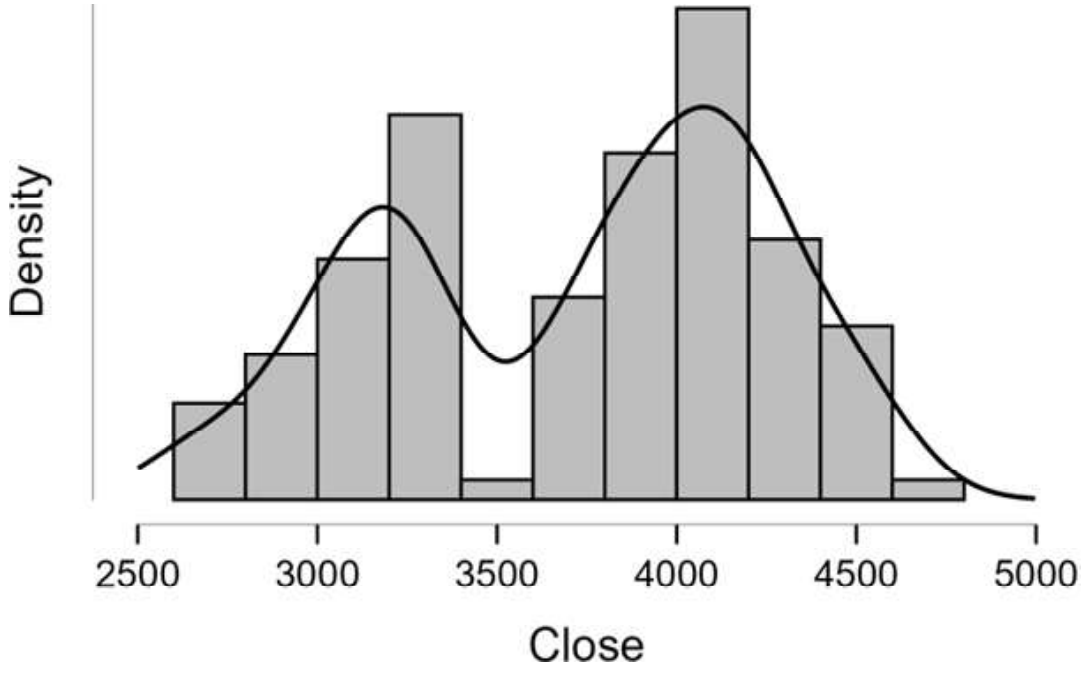
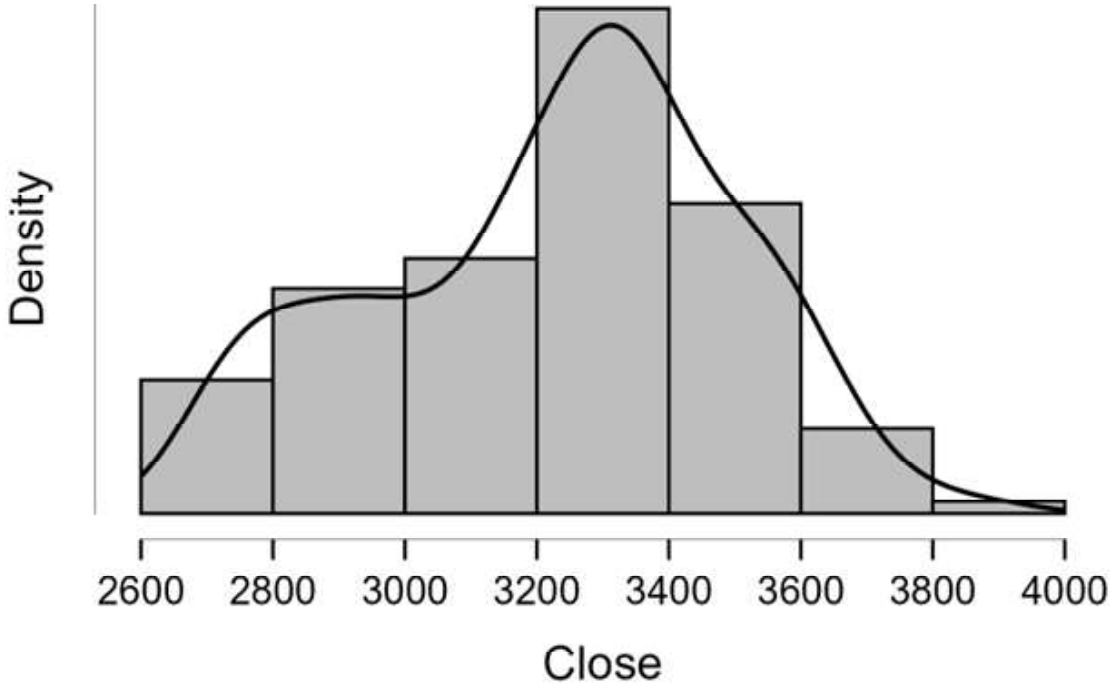


2012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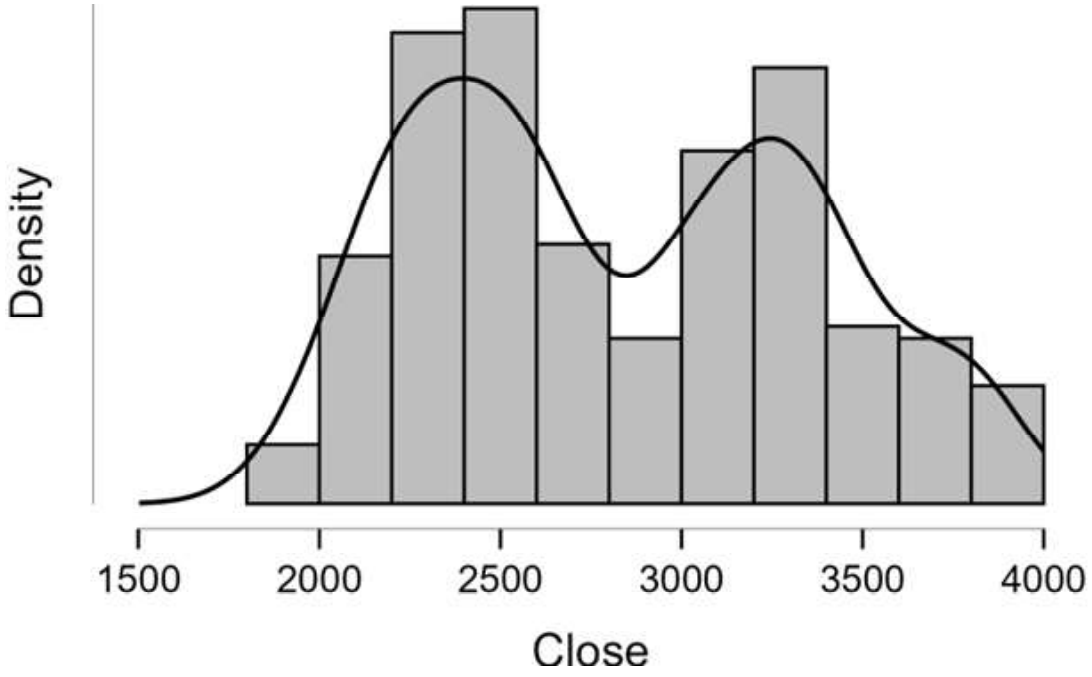
2013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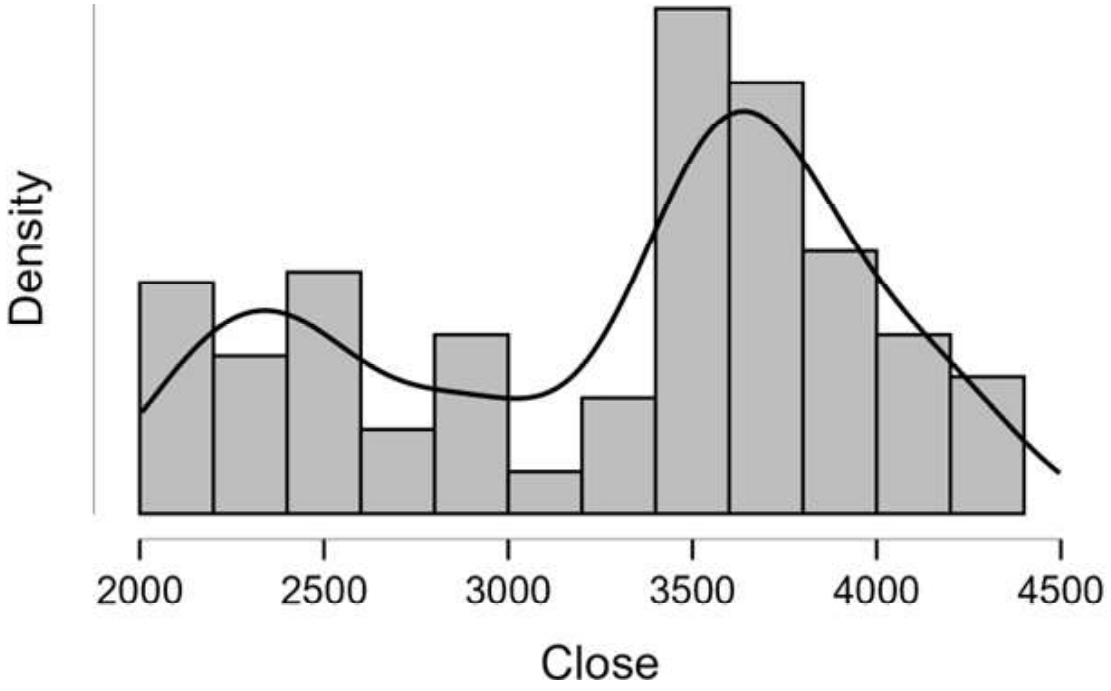
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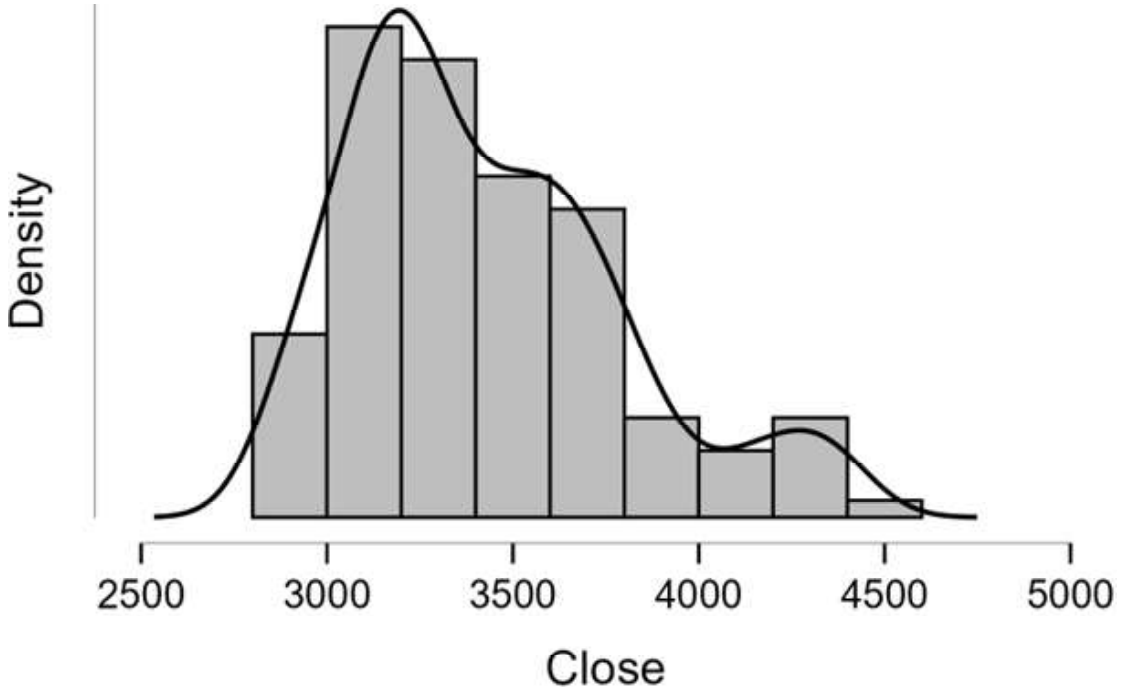
2015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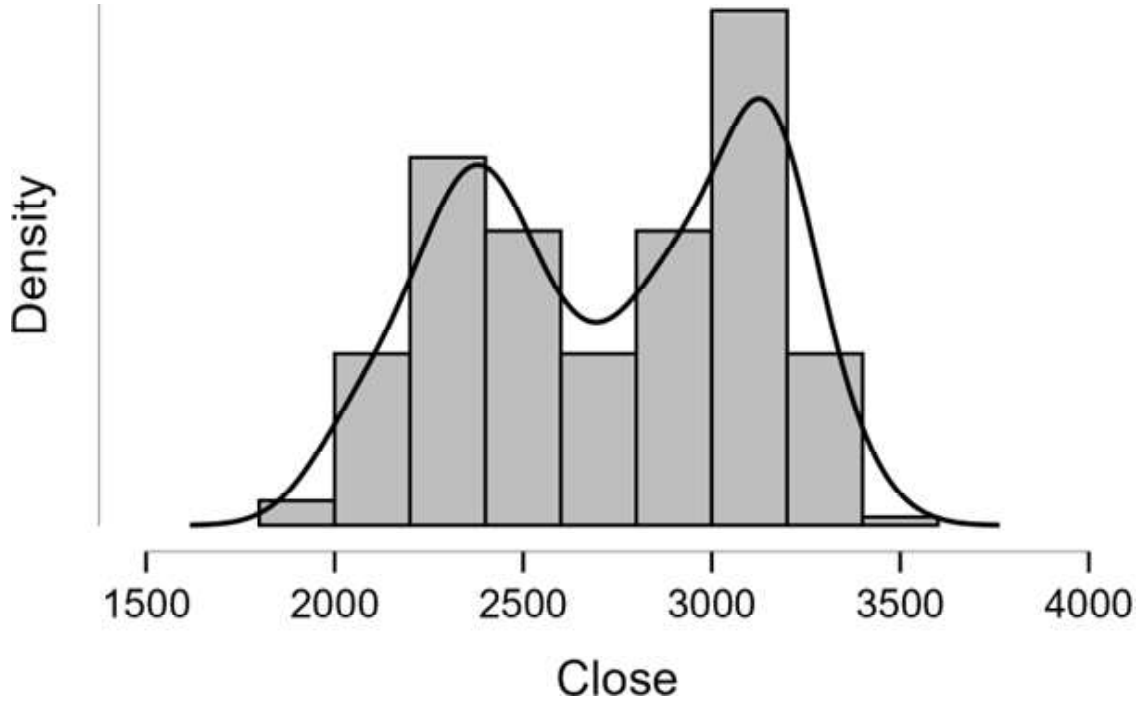
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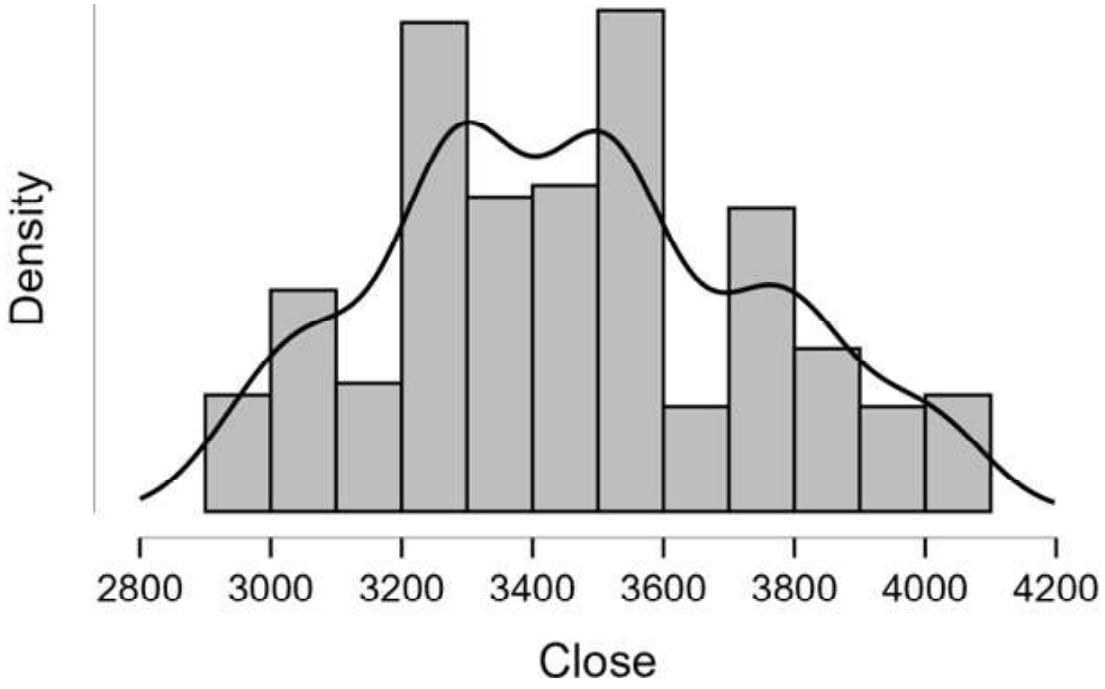
2017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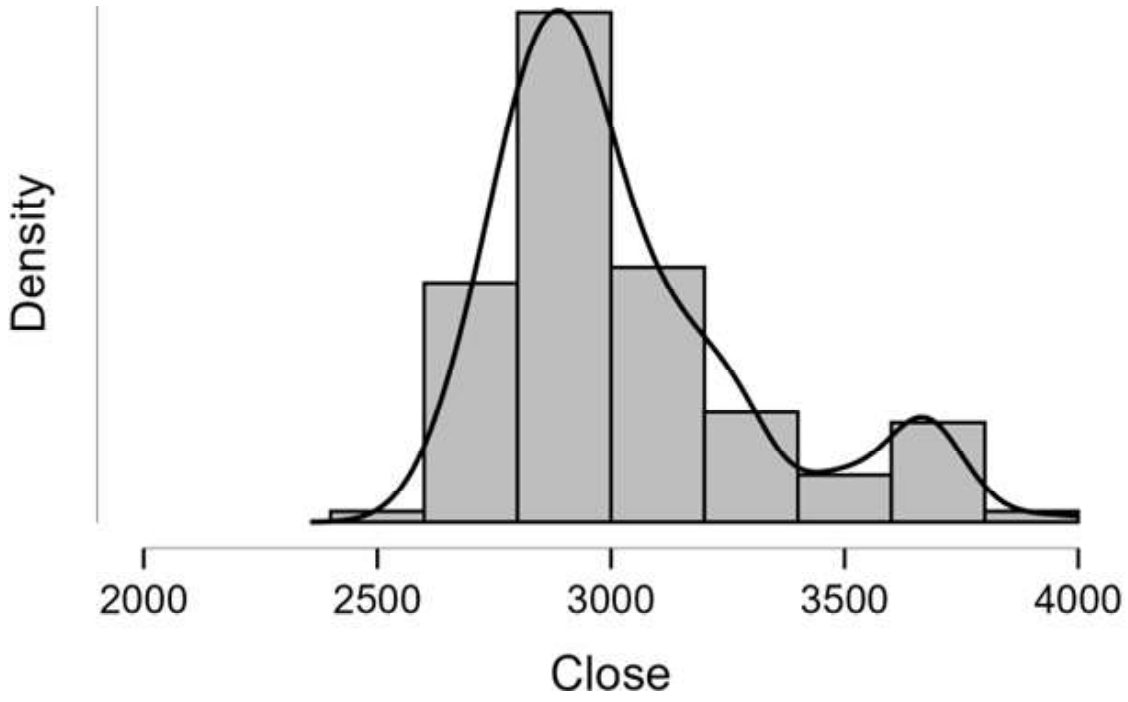
2018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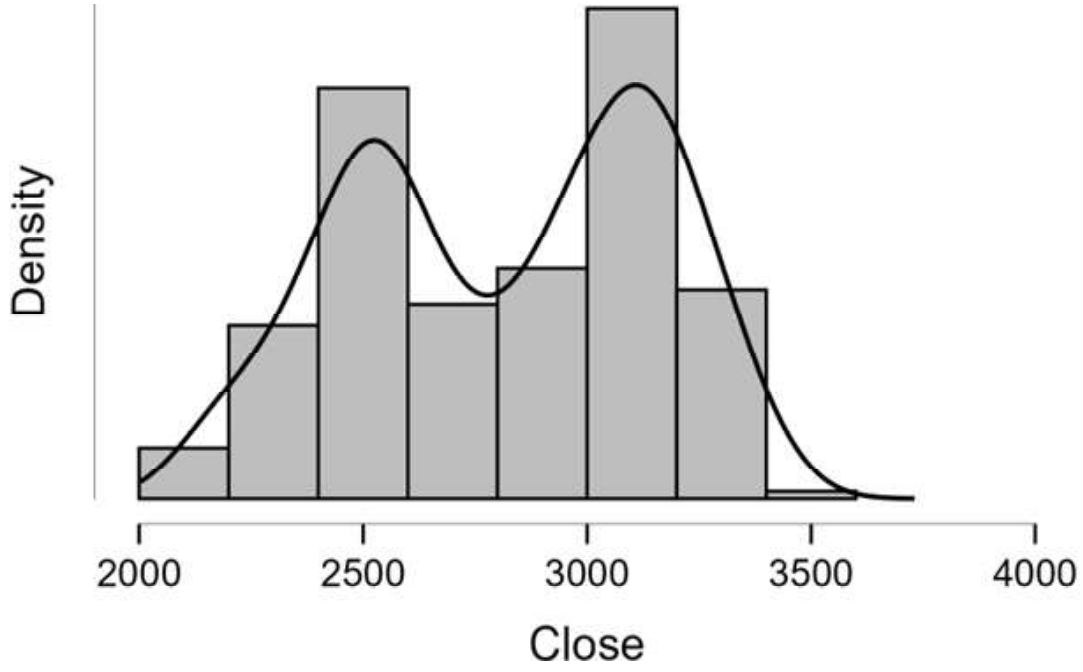
2019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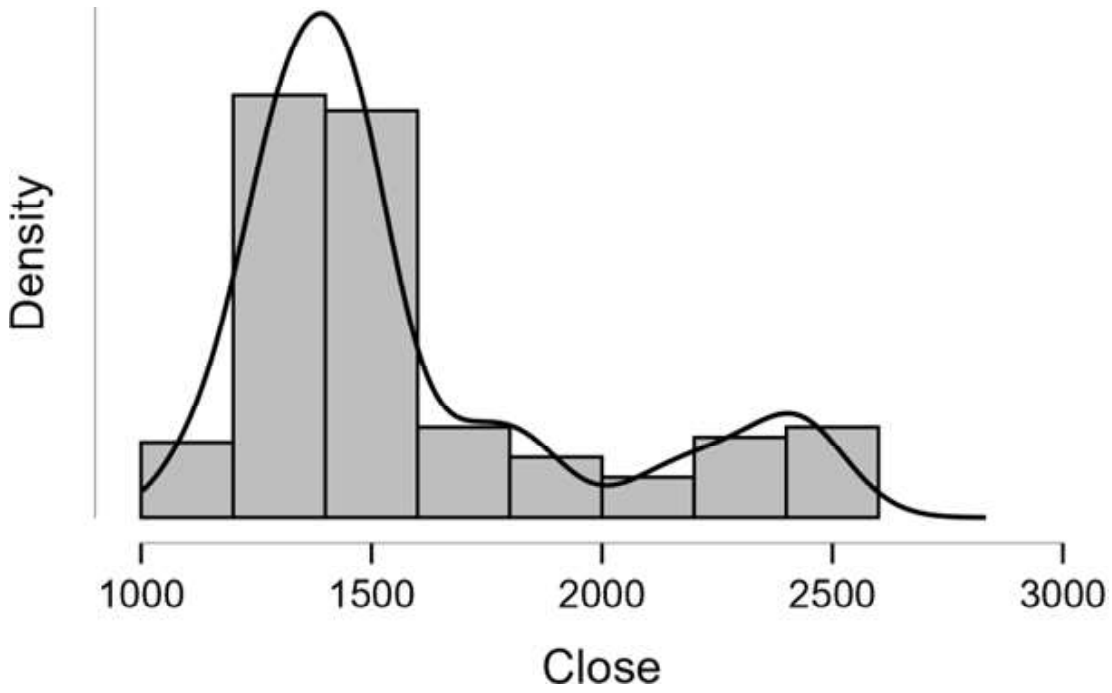
Close

2020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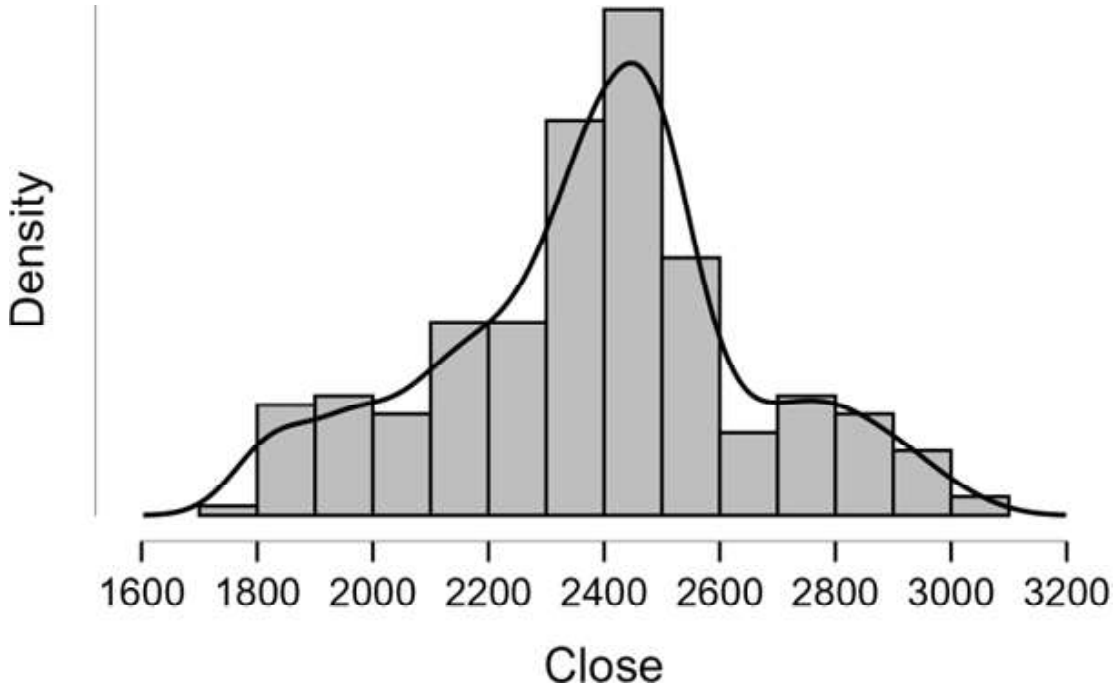
2021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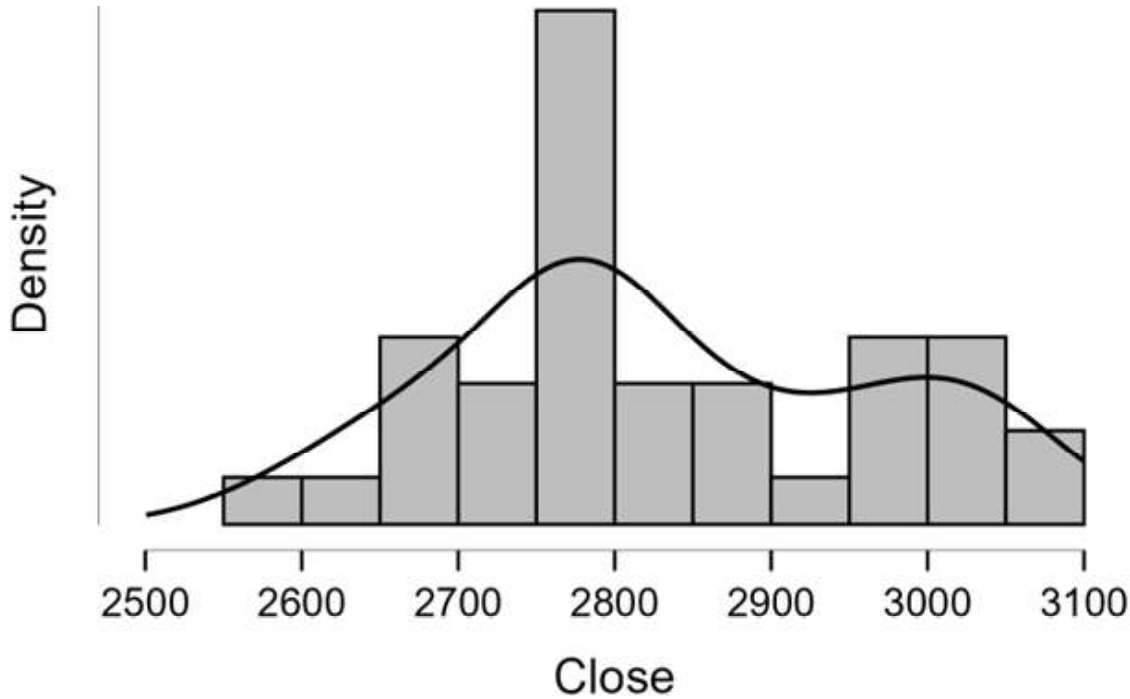
3200
Close



Source: From researcher's data analysis

Table 59 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	0.0732	13.6560	Fréchet	-0.7563	1.3222	Weibull
2011	-0.5547	1.8028	Weibull	-0.1379	7.2515	Weibull
2012	-0.3442	2.9055	Weibull	-0.2220	4.5050	Weibull
2013	-0.2169	4.6096	Weibull	-0.5464	1.8302	Weibull
2014	-0.6283	1.5916	Weibull	-0.0037	272.1427	Weibull
2015	0.0318	31.4315	Fréchet	-0.6993	1.4300	Weibull
2016	-0.4884	2.0474	Weibull	-0.3021	3.3098	Weibull
2017	-0.2384	4.1953	Weibull	-0.4134	2.4191	Weibull
2018	0.1264	7.9088	Fréchet	-0.6512	1.5356	Weibull
2019	-0.5114	1.9554	Weibull	-0.2550	3.9216	Weibull
2020	0.2675	3.7376	Fréchet	-0.7629	1.3108	Weibull
2021	-0.2865	3.4903	Weibull	-0.2501	3.9983	Weibull
2022	-0.2503	3.9951	Weibull	-0.4209	2.3759	Weibull

Source: From researcher's data analysis

Table 60 : Tail index and classification of the Index

	Shape	Scale	
2010	3.719396	2983.3	heavy-tailed and moments of higher order exists
2011	2.847723	2602.9	heavy-tailed and only mean exists
2012	4.790011	2619.4	heavy-tailed and moments of higher order exists
2013	2.726062	1939	heavy-tailed and only mean exists
2014	2.280593	2086.4	heavy-tailed and only mean exists
2015	5.685289	2864.3	heavy-tailed and moments of higher order exists
2016	3.111817	1968	heavy-tailed and moments of higher order exists
2017	5.871481	2916.1	heavy-tailed and moments of higher order exists
2018	6.233248	2572.85	heavy-tailed and moments of higher order exists
2019	3.748771	2150.35	heavy-tailed and moments of higher order exists
2020	2.858888	1087.2	heavy-tailed and only mean exists
2021	3.464808	1783.85	heavy-tailed and moments of higher order exists
2022	10.27305	2584.7	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table 61 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	513.7853	3950.8912	Normal
2011	2	0	399.8816	3713.0071	Normal
2012	2.0000	0.0000	197.6373	3226.9522	Normal
2013	2	0	407.135	2835.438	Normal
2014	2	0	494.8638	3277.6213	Normal
2015	1.853841	1	239.187492	3382.19494	Stable
2016	2.0000	0.0000	304.7558	2728.0754	Normal
2017	2	0	207.4599	3461.6036	Normal
2018	1.3192	1	129.481525	2969.517074	Stable
2019	2	0	262.3764	2815.9081	Normal
2020	1.14444	0.49233	123.775344	1380.758489	Stable
2021	1.88396	-0.2914	180.482805	2392.478171	Stable
2022	2	0	99.23577	2832.4536	Normal

Source: From researcher's data analysis

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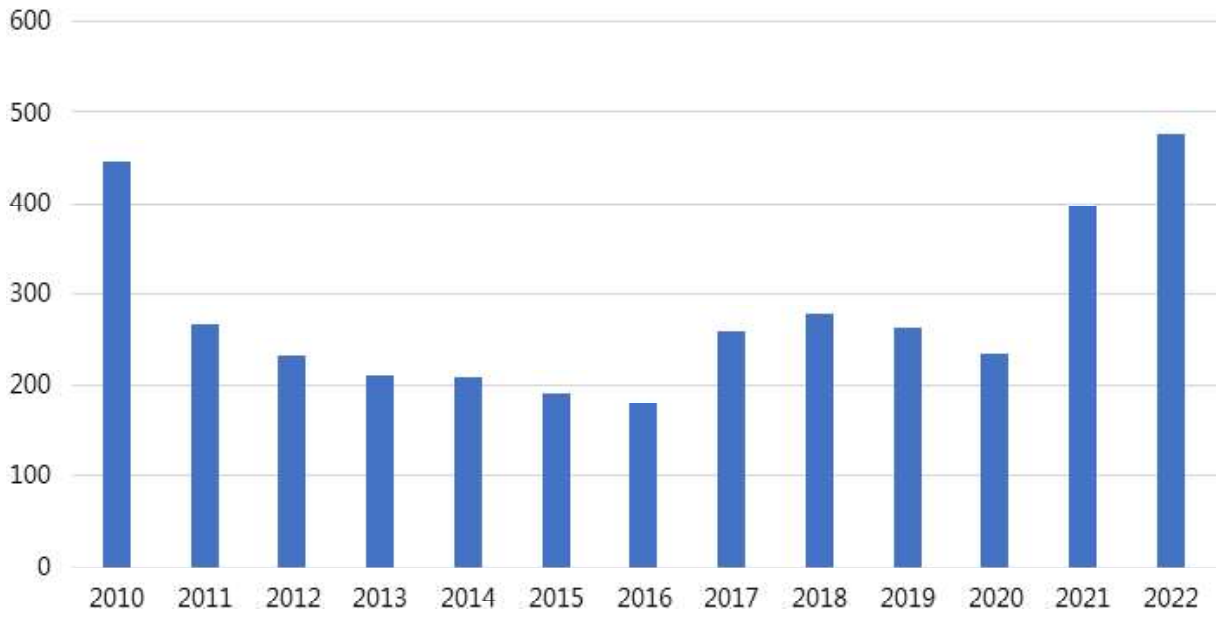
Table 62 : Descriptive Statistics and Test for Normal Probability Model

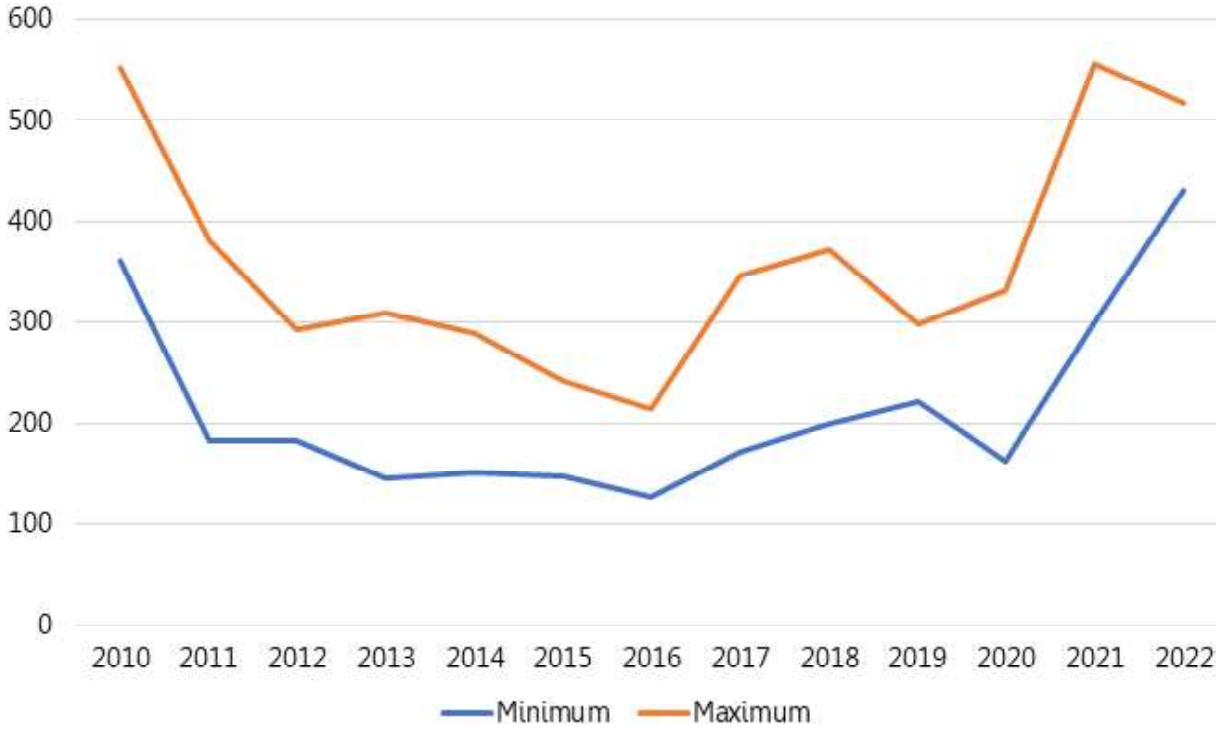
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Valid	252	247	251	250	244	248	247	248	246	245	252	247	37
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	446.057	266.862	233.488	210.288	207.916	191.684	178.885	258.419	279.15	262.358	233.781	396.825	477.074
Std. Deviation	44.547	39.392	23.215	46.295	33.551	23.948	24.444	44.459	42.633	19.031	48.616	77.444	22.437
Coefficient of Variation	0.1	0.148	0.099	0.22	0.161	0.125	0.137	0.172	0.153	0.073	0.208	0.195	0.047
Skewness	0.048	0.119	0.338	0.52	0.131	0.502	-0.148	-0.392	-0.012	-0.461	0.6	0.652	-0.25
Std. Error of Skewness	0.153	0.155	0.154	0.154	0.156	0.155	0.155	0.155	0.155	0.156	0.153	0.155	0.388
Kurtosis	-0.606	-0.124	-0.385	-1.048	-0.92	-1.076	-1.206	-0.833	-0.875	-0.723	-0.934	-1.045	-0.879
Std. Error of Kurtosis	0.306	0.309	0.306	0.307	0.31	0.308	0.309	0.308	0.309	0.31	0.306	0.309	0.759
Shapiro-Wilk	0.984	0.986	0.979	0.91	0.97	0.913	0.926	0.937	0.972	0.955	0.903	0.873	0.968
P-value of Shapiro-Wilk	0.007	0.018	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	0.36
Minimum	360.2	183	183.1	146.7	151.3	148.05	128.25	172.6	200.1	221.2	162.15	300.3	430
Maximum	552.34	381.35	293.85	310.15	288.95	241.1	214.65	346.9	372.25	298.55	331.05	556.15	516.1

Source: From researcher's data analysis



Graph 29 : Mean values of the index

Source: From researcher's data analysis

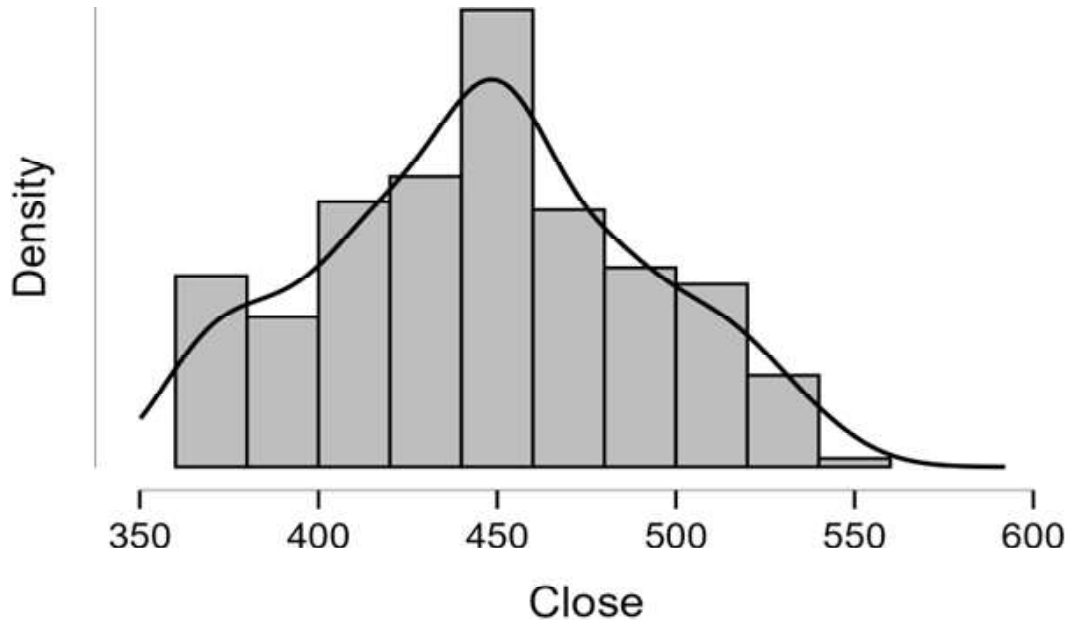


Graph 30 : Maximum and Minimum values of the Index

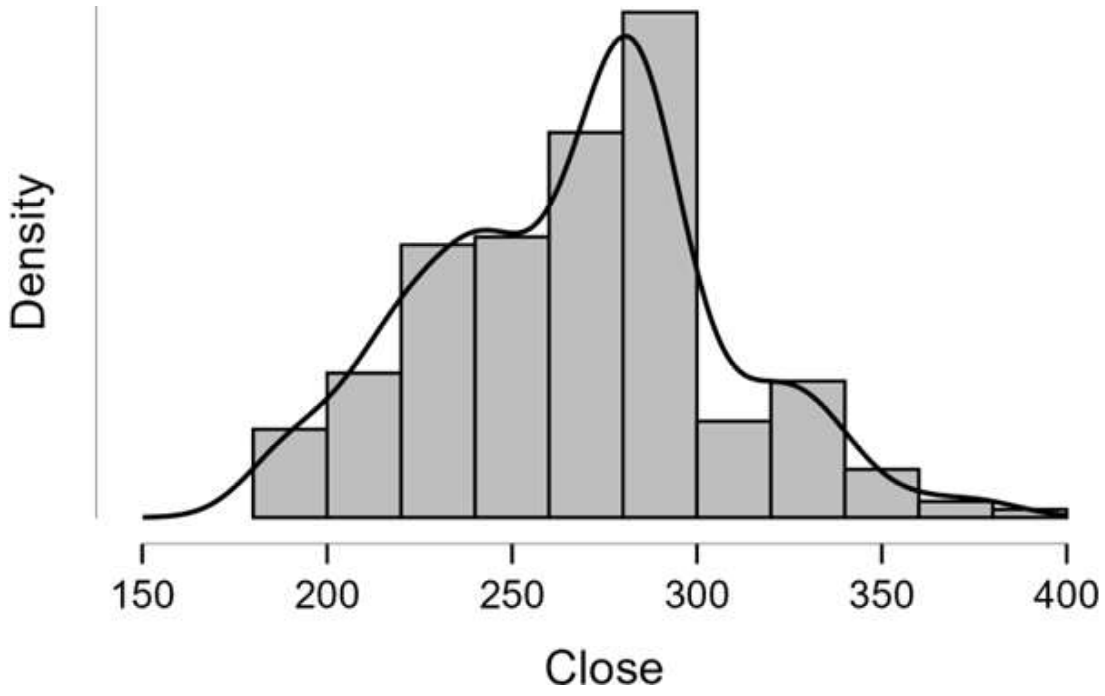
Source: From researcher's data analysis

Distribution Plots

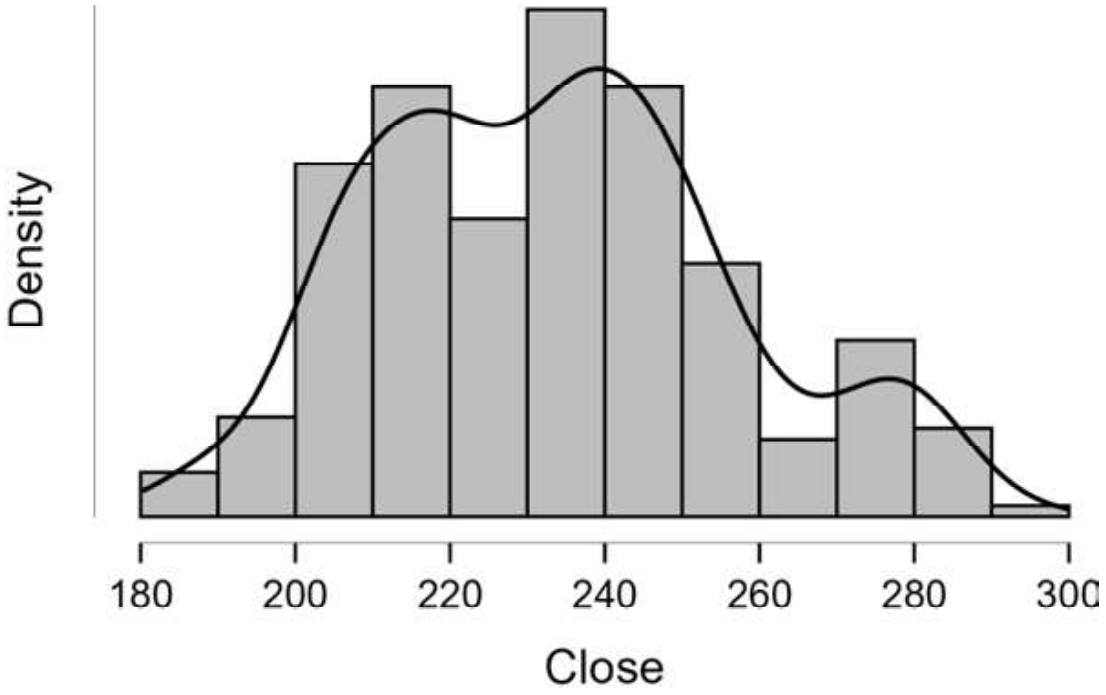
2010



2011



2012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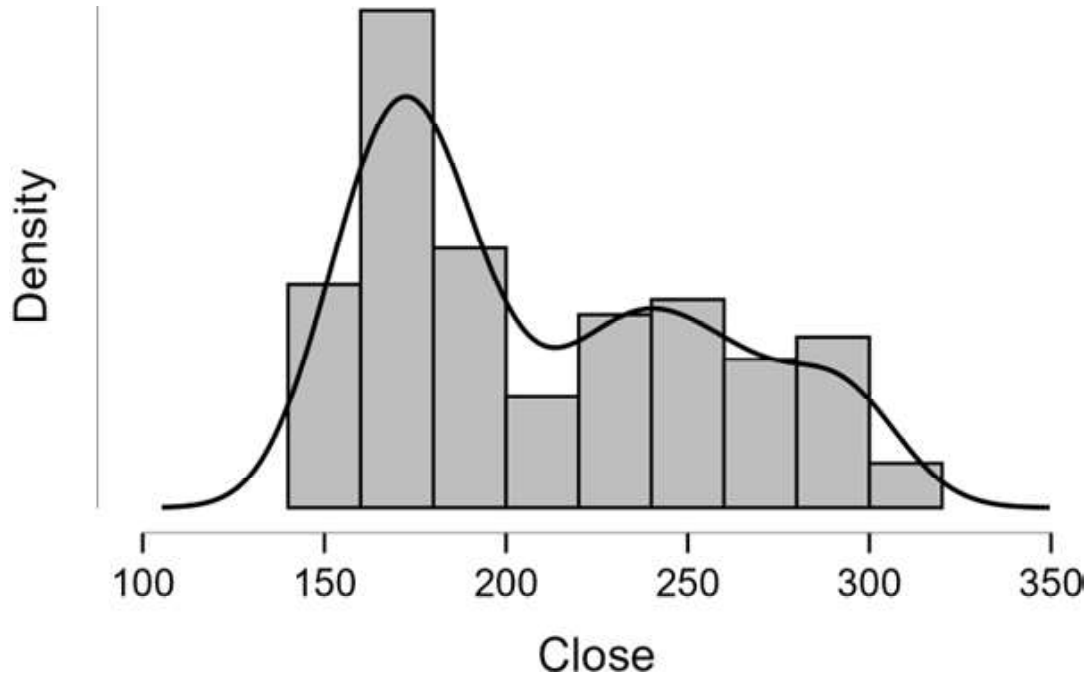
2013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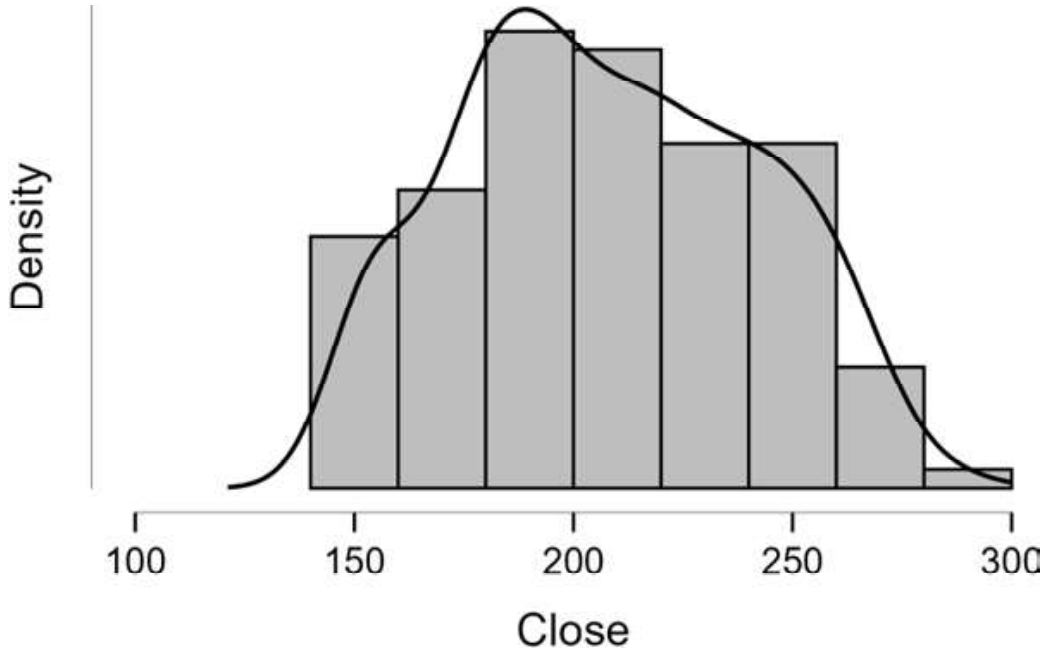
2014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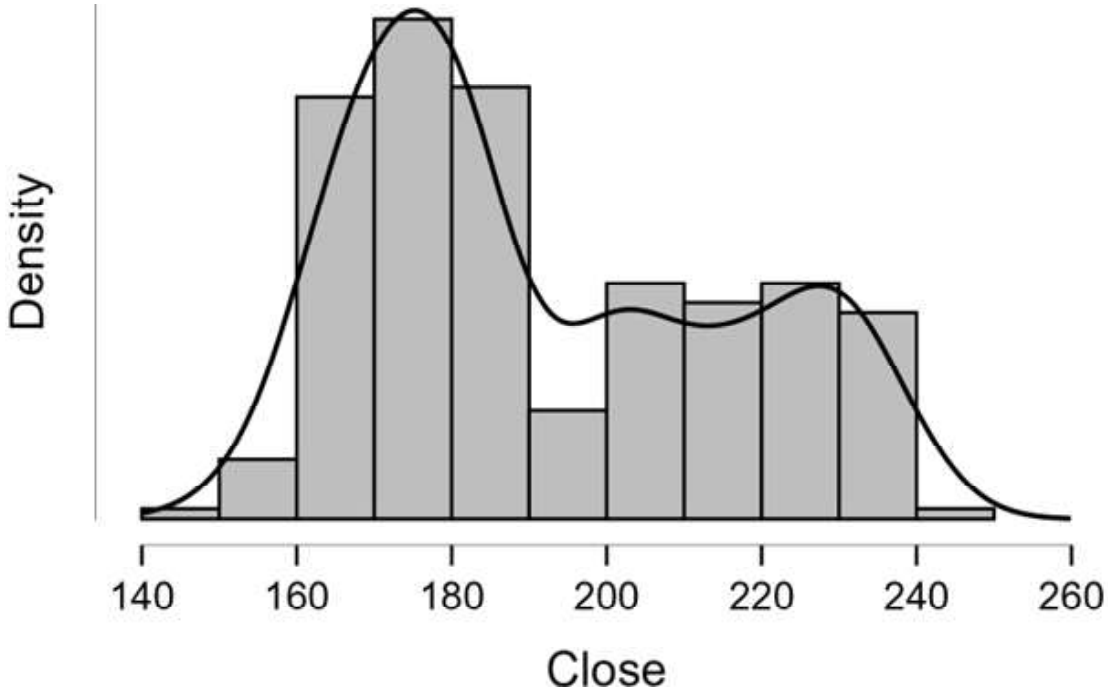
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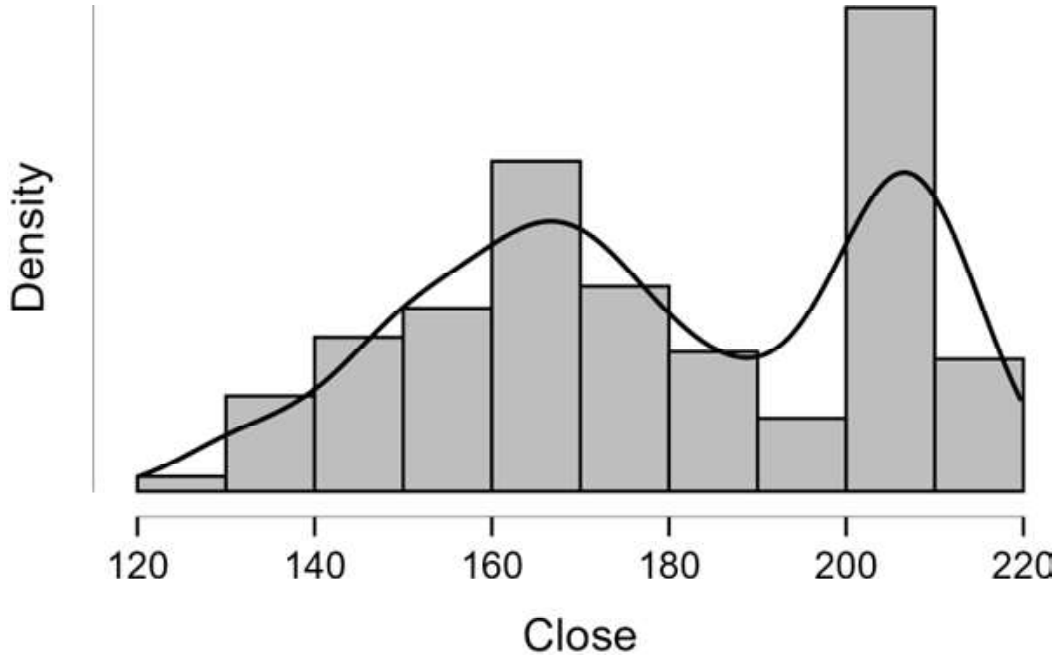
2016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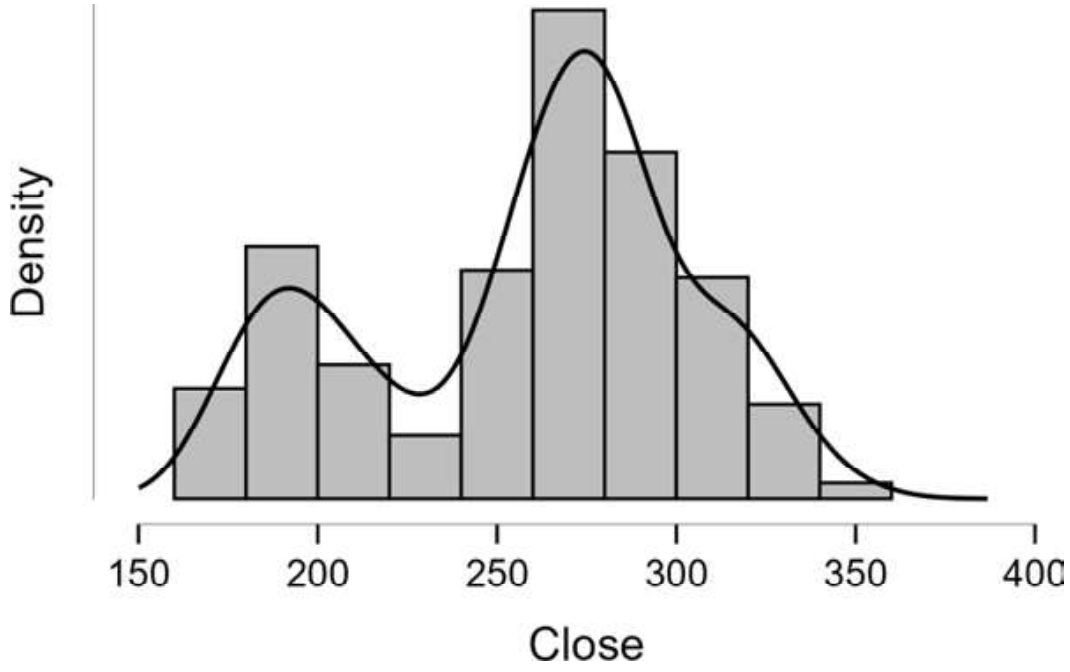
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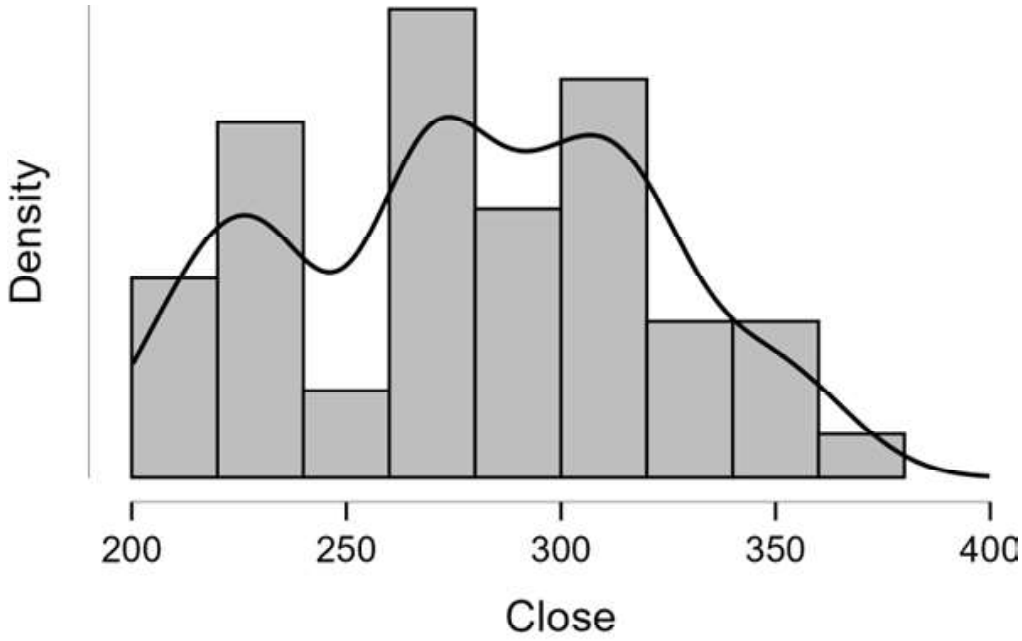
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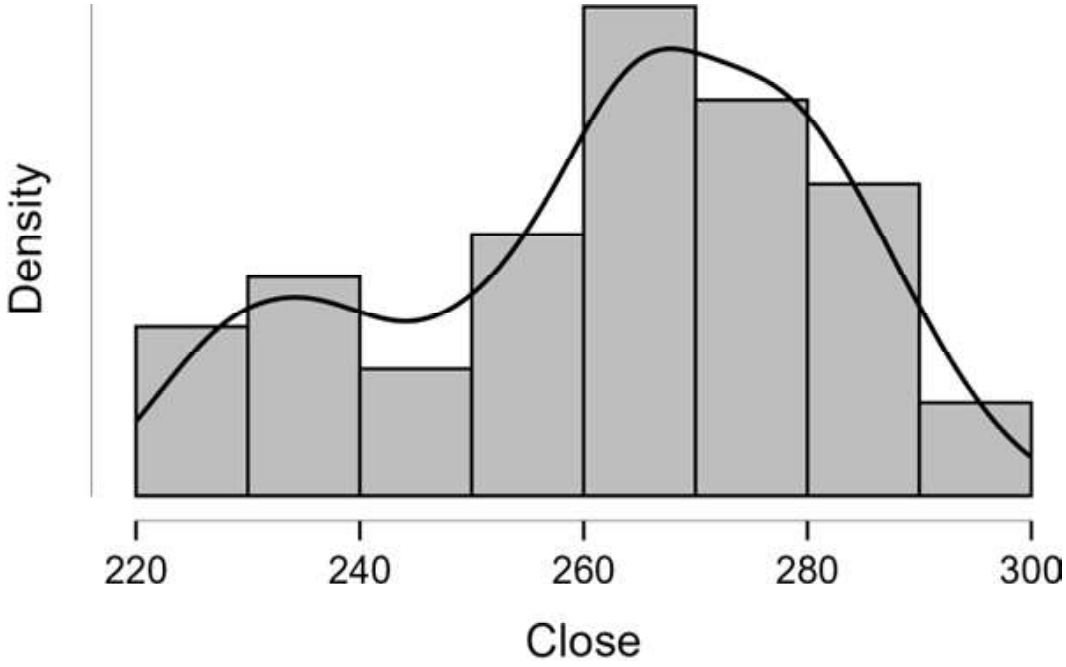
2019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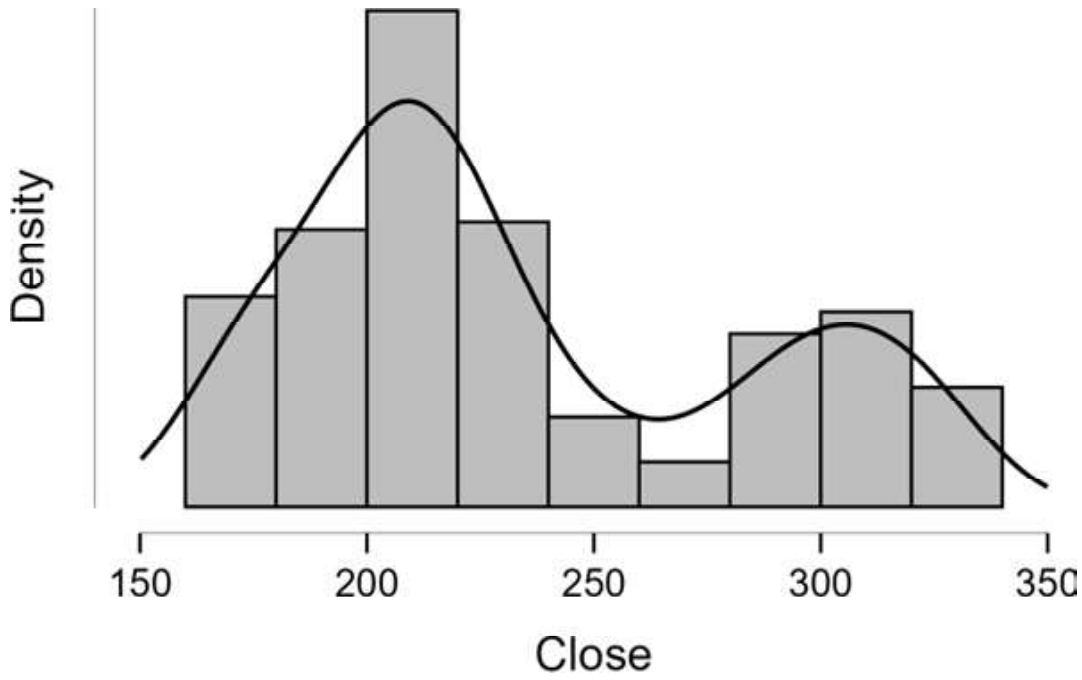
2020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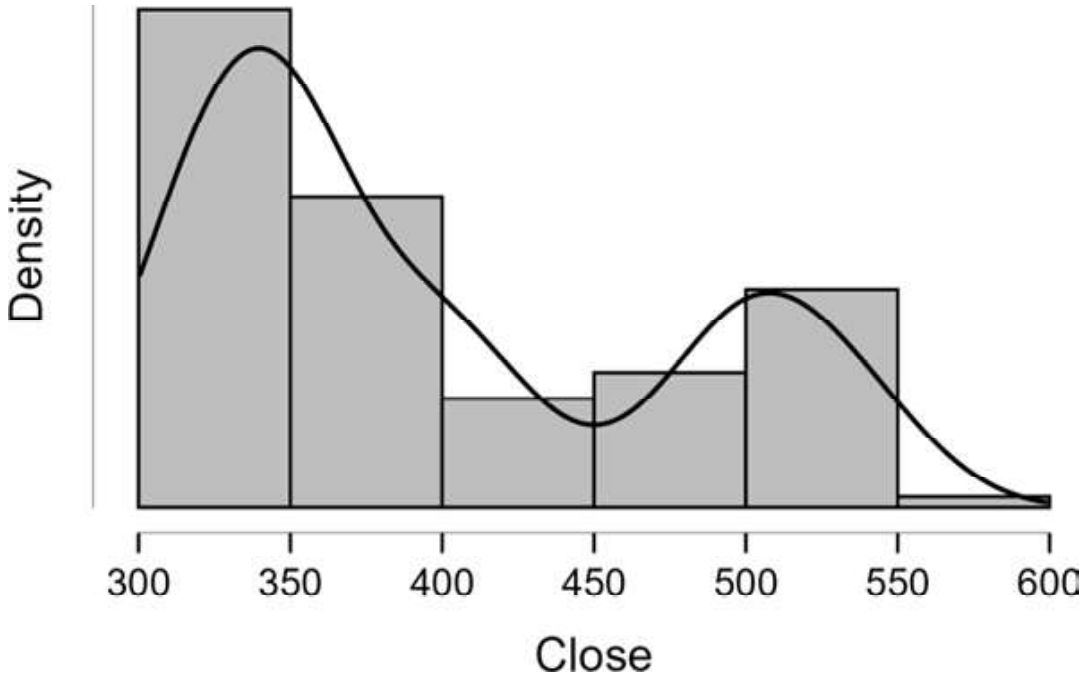
2021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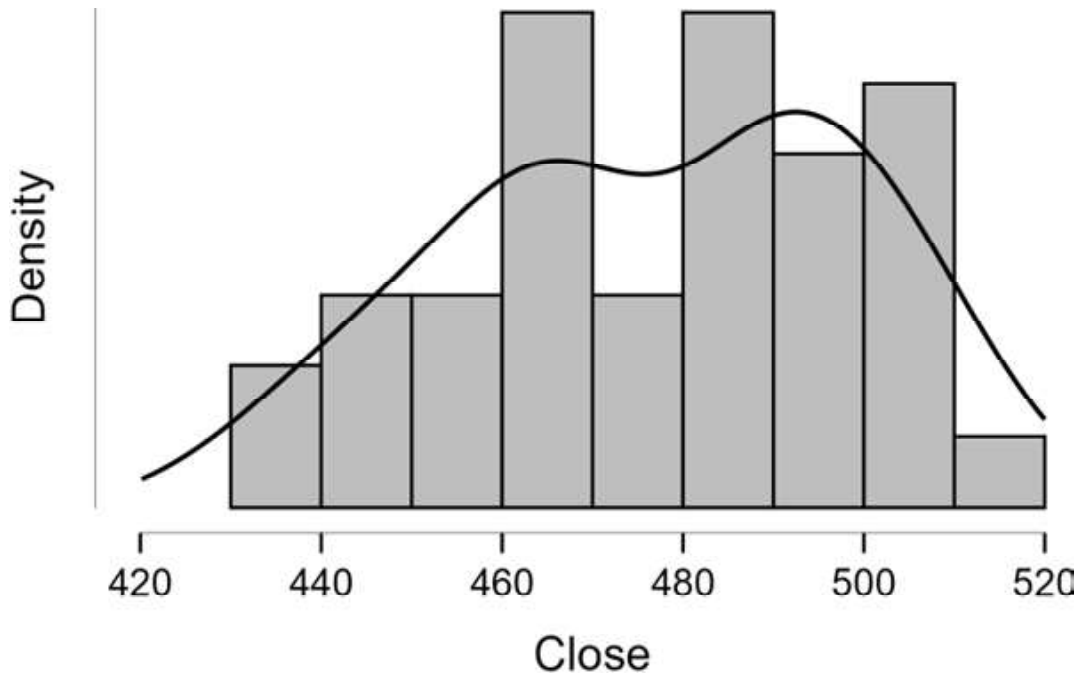

Source: From researcher's data analysis

Table 63 : Model for minimum and maximum index variable

	Maximum			Minimum		
	Xi	Index	Model	Index	Index	Model
2010	-0.2915	3.4307	Weibull	-0.3532	2.8316	Weibull
2011	-0.2309	4.3314	Weibull	-0.3409	2.9334	Weibull
2012	-0.1804	5.5432	Weibull	-0.3923	2.5489	Weibull
2013	0.2141	4.6706	Fréchet	-0.7507	1.3321	Weibull
2014	-0.2708	3.6932	Weibull	-0.4512	2.2161	Weibull
2015	0.0703	14.2186	Fréchet	-0.4814	2.0773	Weibull
2016	-0.7419	1.3479	Weibull	-0.2643	3.7839	Weibull
2017	-0.4444	2.2503	Weibull	-0.1363	7.3363	Weibull
2018	-0.3284	3.0452	Weibull	-0.3729	2.6818	Weibull
2019	-0.4786	2.0894	Weibull	-0.0903	11.0794	Weibull
2020	0.1026	9.7512	Fréchet	-0.6713	1.4898	Weibull
2021	0.3559	2.8097	Fréchet	-0.8555	1.1689	Weibull
2022	-0.47662	2.0981	Weibull	-0.2066	4.8402	Weibull

Source: From researcher's data analysis

Table 64 : Tail index and classification of the Index

	Shape	Scale	Comments based on index values
2010	4.718448	360.2	heavy-tailed and moments of higher order exists
2011	2.687987	183	heavy-tailed and only mean exists
2012	4.132693	183.1	heavy-tailed and moments of higher order exists
2013	2.9238	146.7	heavy-tailed and only mean exists
2014	3.225588	151.3	heavy-tailed and moments of higher order exists
2015	3.923517	148.05	heavy-tailed and moments of higher order exists
2016	3.040428	128.25	heavy-tailed and moments of higher order exists
2017	2.538597	172.6	heavy-tailed and only mean exists
2018	3.064939	200.1	heavy-tailed and moments of higher order exists
2019	5.853145	221.2	heavy-tailed and moments of higher order exists
2020	2.852898	162.15	heavy-tailed and only mean exists
2021	3.777895	300.3	heavy-tailed and moments of higher order exists
2022	9.010719	430	heavy-tailed and moments of higher order exists

Source: From researcher's data analysis

Table65 : Index value for Stable Models

	α	β	σ	μ	Model
2010	2	0	32.7589	446.1062	Normal
2011	2	0	27.97921	266.94956	Normal
2012	2	0	16.6706	233.6998	Normal
2013	2	0	34.54804	210.93011	Normal
2014	2	0	25.33114	208.02544	Normal
2015	2	0	17.86653	192.01119	Normal
2016	2	0	18.9877	178.8060	Normal
2017	2	0	32.68008	257.92121	Normal
2018	2	0	32.15407	279.12405	Normal
2019	2	0	13.85188	262.11195	Normal
2020	2	0	35.28591	234.62959	Normal
2021	2	0	56.36571	398.29072	Normal
2022	2	0	16.71796	476.94073	Normal

Source: From researcher's data analysis

Discussion Based on the results of the analysis

Table 66 : Index values for the sectoral Indices

Index Name	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
NIFTY Auto Index	4.83	9.46	4.92	7.20	3.21	8.75	4.32	7.64	4.76	5.90	2.09	8.13	26.79
NIFTYBank Index	4.44	3.61	3.65	3.63	2.83	7.29	3.88	3.94	10.14	10.04	2.77	6.41	22.23
NIFTY Financial Services Index	-	7.42	4.06	4.08	3.19	8.01	4.24	3.85	11.08	7.31	2.88	6.64	17.96
NIFTY Financial Services 25/50 Index											5.36	6.01	17.21
Nifty Financial Services Ex Bank	4.83	5.04	3.86	4.19	3.17	12.18	3.84	3.23	5.16	6.68	2.58	5.36	12.24
NIFTY FMCG Index	5.75	5.76	4.59	7.77	8.48	13.33	7.70	5.65	9.60	16.28	3.83	8.70	25.27
NIFTY Healthcare Index	5.21	15.84	6.82	7.87	5.69	6.54	8.41	7.23	-	-	16.27	5.50	16.69
NIFTY IT Index	7.76	4.45	9.08	4.54	6.22	14.15	7.75	11.86	5.36	10.36	2.36	4.66	12.55
NIFTY Media Index	8.39	5.22	5.35	7.52	5.93	7.40	5.55	6.16	4.24	5.08	2.59	3.88	10.40
NIFTY Metal Index	-	4.41	7.79	3.14	3.81	3.48	2.57	5.19	6.23	4.63	2.37	2.16	16.82
NIFTY Pharma Index	5.13	13.27	6.95	6.39	18.65		7.47	7.22	7.11	6.36	2.26	5.96	18.51
NIFTY Private Bank Index	4.31	4.68	3.19	3.48	2.87	7.52	3.93	3.90	10.37	9.76	2.53	8.26	26.49
NIFTY PSU Bank Index	3.72	2.85	4.79	2.73	2.28	5.69	3.11	5.87	6.23	3.75	2.86	3.46	10.27
NIFTY Realty Index	4.72	2.69	4.13	2.92	3.23	3.92	3.04	2.54	3.06	5.85	2.85	3.78	9.01
NIFTY Consumer Durables Index	3.90	6.04	3.98	5.39	2.72	10.22	8.85	2.92	-	-	3.10	4.43	15.83
NIFTY Oil and Gas Index											2.38	7.12	22.18

Source: Based on the data analysis

From the results presented on the test for normality, one can observe that except for a few years the normality assumption is not satisfied by the data. The above table gives the summary of the tail index values for all the sectoral indices. One can observe that the tail indexes for the sectors for almost all the sectors are more than 3, which indicates that the tails are heavy-tailed. But, the good part is that the moments of higher-order exists for all the sectors for almost all the years.

The year 2020, which is a year that was hit by COVID-19 had decreased the index values for almost all the sectors except for Health care and financial services. This may be due to the drastic increase in the requirement of the medical facilities and also the financial transactions that have taken place during this time.

The sector which has the lowest tail index value is the one that will have the heaviest tail and more density at the tails. For such sectors, the mean value doesn't exist. Such sectors are said to have got affected the most and all those sectors that have a tail index of less than 3 can be listed from the above table. Among the other sectors, the AUTO, IT, Pharma Oil and Gas sectors have the heavies tail and mean doesn't exist for these sectors and are highly affected by the crisis. One can observe that almost all the sectors have an index value of less than 3, but these sectors are classified as those that are highly affected. During the year 2022, the index values for all the sectors have increased and this is an indication of the revival of the sectors from the COVID-19 crisis. This also indicates that the events have a high impact on the sectoral indices. Monitoring these events continuously and taking the right decisions may improve the performance of the sectors in the market. For example, the announcement of health packages by the government of India during the COVID-19 crisis and also allotment of huge funds towards medical and other allied sectors during the budgets have improved the performance of the sectors. Similarly, one can make the right decisions to improve the performance of those sectors that have got affected by the events. The process suggested through this study on the sectoral indices will help one to identify the sectors that have got affected severely during the given time horizon and motivate one to search for the events that are the root cause for the heavy tails and failure of the normal model.

We now compute the stable index for the cumulative sectoral index variables and observe if the sectoral could sustain the shocks caused due to the events. The table below gives the stable index values for all the sectoral indices. If the stable index is close to 2 are equal to 2, then we conclude that the normal model is preserved by the cumulative index variable and the values generated by other events have neutralized the impact generated by the critical events. In other words, other events have balanced the critical events and this process will help one to identify those sectors that could sustain the shocks generated by the events.

Table 67 : Stable Index values for the sectoral Indices

Index Name	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
NIFTY Auto Index	2.0000	1.9979	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	1.7499	1.9878	2.0000	1.9371	1.9434
NIFTYBank Index	2.0000	2.0000	1.9683	2.0000	2.0000	2.0000	2.0000	1.9895	2.0000	2.0000	2.0000	1.9877	1.9909
NIFTY Financial Services Index		2.0000	1.9830	1.9915	2.0000	2.0000	2.0000	1.9874	2.0000	2.0000	2.0000	2.0000	2.0000
NIFTY Financial Services 25/50 Index											2.0000	2.0000	2.0000
Nifty Financial Services Ex Bank	2.0000	2.0000	1.8534	2.0000	2.0000	2.0000	2.0000	1.9658	1.9699	2.0000	2.0000	2.0000	2.0000
NIFTY FMCG Index	2.0000	1.9738	2.0000	2.0000	2.0000	1.8821	2.0000	2.0000	2.0000	1.9646	1.1374	2.0000	2.0000
NIFTY Healthcare Index	2.0000	1.9825	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000			2.0000	2.0000	2.0000
NIFTY IT Index	1.8975	2.0000	2.0000	2.0000	2.0000	1.9470	2.0000	2.0000	2.0000	1.9224	2.0000	2.0000	2.0000
NIFTY Media Index	2.0000	2.0000	1.7693	2.0000	2.0000	2.0000	2.0000	1.4671	2.0000	2.0000	2.0000	2.0000	1.8865
NIFTY Metal Index		1.9846	1.7916	1.8562	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	1.9062	2.0000
NIFTY Pharma Index	2.0000	1.9284	2.0000	2.0000	2.0000		1.7277	2.0000	2.0000	2.0000	2.0000	1.9797	2.0000
NIFTY Private Bank Index	2.0000	2.0000	1.9250	1.8850	2.0000	2.0000	2.0000	1.9981	2.0000	2.0000	2.0000	1.9385	2.0000
NIFTY PSU Bank Index	2.0000	2.0000	2.0000	2.0000	2.0000	1.8538	2.0000	2.0000	1.3192	2.0000	1.1444	1.8840	2.0000
NIFTY Realty Index	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
NIFTY Consumer Durables Index	2.0000	2.0000	0.8538	2.0000	2.0000	2.0000	2.0000	1.9980			1.9624	2.0000	2.0000
NIFTY Oil and Gas Index											1.1777	1.9801	2.0000

Source: Based on the data analysis

From the above table, one can note that FMCG, PSU bank and Oil and Gas sectors could not sustain the shocks and all the other sectors could sustain the shocks. The media index could not sustain the shocks in the year 2022.

The second objective of the study is to identify the extreme value distribution that best suits the extreme sectoral index variables (Maximum and minimum). The following table gives the results of the same.

Table 68 : Distribution of the Maximum Index variable

Index Name	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
NIFTY Auto Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTYBank Index	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Financial Services Index		Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Financial Services 25/50 Index											Fréchet	Weibull	Weibull
Nifty Financial Services Ex Bank	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY FMCG Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Healthcare Index	Weibull	Fréchet	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull			Weibull	Weibull	Weibull
NIFTY IT Index	Fréchet	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet	Fréchet
NIFTY Media Index	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull
NIFTY Metal Index		Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Pharma Index	Weibull	Weibull	Weibull	Weibull	Weibull		Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Private Bank Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY PSU Bank Index	Fréchet	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull	Fréchet	Weibull	Fréchet	Weibull	Weibull
NIFTY Realty Index	Weibull	Weibull	Weibull	Fréchet	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Fréchet	Fréchet	Weibull
NIFTY Consumer Durables Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull			Weibull	Weibull	Weibull
NIFTY Oil and Gas Index											Weibull	Weibull	Weibull

Source: Based on the data analysis

Table 69 : Distribution of the Minimum Index variable

Index Name	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
NIFTY Auto Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull
NIFTYBank Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Financial Services Index		Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Financial Services 25/50 Index											Weibull	Weibull	Weibull
Nifty Financial Services Ex Bank	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY FMCG Index	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Healthcare Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull			Fréchet	Fréchet	Weibull
NIFTY IT Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Media Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Metal Index		Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull
NIFTY Pharma Index	Weibull	Weibull	Weibull	Weibull	Weibull		Fréchet	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull
NIFTY Private Bank Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Fréchet	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY PSU Bank Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Realty Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
NIFTY Consumer Durables Index	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull			Weibull	Weibull	Weibull
NIFTY Oil and Gas Index											Fréchet	Weibull	Weibull

Source: Based on the data analysis

The above two tables give the distributions that suit the maximum and the minimum index variables. Weibull distribution is the appropriate distribution that suits the maximum and minimum index variables for almost all the years. Fréchet distribution is appropriate in a few cases. Using these two models one can compute the respective probabilities. An interesting aspect is, having Fréchet distribution as an appropriate distribution. The tails of the Fréchet distribution are regularly varying and heavy-tailed. This indicates that the events have changed the behaviour of the extremes. Whereas the tails of Weibull are thin tail and indicates that the events haven't impacted much the behaviour of the extreme index variables.

Framework for Practitioners

We present the following framework for the practitioners, based on the results obtained through the data analysis.

Based on the Descriptive Statistics and Test for Normality

One can observe the mean and standard deviation to note the level the closing index value reaches every year along with the deviation. Together, one can construct the interval to understand the spread and to the extent, the mean value either increases or decreases. This can be used to decide on the sector concerning its reaction to the information generated around the same. If the information generated has a positive impact, then there is a high chance of its mean value crossing a given threshold indicating a positive sign for investment in that sector. Similarly, one can also use the same for avoiding the sector for investment in case of decrement. If the deviation is low, then it is an indication of the consistency of the index values from its mean and the intervals will be narrow, indicating the estimate to the close to the unknown value of the index. Standard deviation can be used to check if the volatility of the considered sector is high, medium or low. High volatility is desired in case one is interested to understand the behaviour of the sector better. That is, one can understand how an index reacts to the information generated better if the volatility is high. In case one is interested to identify an index that is consistent over time, then it is desired to have low volatility. Similarly, the minimum and maximum values give the range between which the value of the index are fluctuating. It is expected to have a low range, in case of low volatility and, a high range, in case of high volatility.

The test for normality helps one to know the level of fluctuation generated by the information on the index. If the information generated has a high impact, then the index data do not satisfy the assumption of normality, indicating that the impact has distorted the normal tail behaviour and increased the density at the tails, leading to heavy tails. In such cases, the decision-makers can study the index in depth by estimating the tail index value. Based on the tail index value, the decision-makers can conclude on the existence of the moments of the index variable. This process helps the decision-makers to note the fluctuation of the index between the normal and the non-normal behaviour of the index variable. If the frequency of the fluctuation is high, then it is not advised to invest in the stocks under that sector. A decision on the same can be taken only after carefully observing the individual movements of the stocks listed under the sectoral index considered.

Hence, we suggest the practitioners compute the descriptive statistics and observe the changes in the mean levels of the index variable along with

the volatility, followed by the test for normality. A combination of these will help the decision-makers to have a better understanding of the sectors they wish to consider for investments.

Based on the Tail Index Estimation

From the results of the data analysis, we suggest that practitioners study and understand the change in tail behaviour of the index of interest with time. This will help them to observe if the events associated with the time have a significant impact on the index or not? In case the events have a significant impact, then they increase the density at the tails, leading to a heavy tail behaviour. Knowing this will help them to continuously monitor such events and take decisions that will make the stocks sustains the shocks created by these events. In a way, this process will help to identify the critical events that impact the movements of the index and take appropriate decisions to decrease the impact of these events on the stocks. Hence, estimating the tail index is suggested as one of the key aspects as part of the stock market analysis, when the normality is not preserved.

The flow of the analysis can move from the descriptive analysis, test for normality to estimation of the index.

Based on the Extremal Index Estimation

The next step in the analysis one can consider is the estimation of the extremal tail index. This will help the practitioners in identifying the extreme value distribution associated with the maximum and the minimum index variables. Identifying the models for the extremes will help one to measure the probability of the extremes crossing a threshold. Once a model is identified, calculations on the respective stocks can be done using the data, and monitor the changes in the probabilities. If the probabilities are high (low), then a decision on the investment can be made.

This step can be added to the flow of the nalysis after the tail index estimation was made.

Based on the Stable Index Estimation

We would recommend this step as the most important step in the flow of the analysis. As indicated, failure of the normality leads to a conclusion that the impact of the events is high on the stocks. But, sometimes the impact can be neutralized if the aggregate values are considered. This is because the high impact caused due to a few events can be balanced by the positive impact caused due to other events. The same can be identified by considering the cumulative index variable. When normality is not satisfied by the data of a particular index, it is suggested through this study to estimate the stable index and check if the cumulative index is close to a normal index or a stable index. If the index value is close to a normal index, then one can adopt a normal model to study the behaviour of the index. This is because sometimes the test procedures may not reveal how close the index behaviour is to a normal model. In such cases estimating the stable index will help the decision-makers. We propose this as an important step in the stock market analysis. This will also inform the extent to which an event(s) can impact the behaviour of an index. If the impact is low, then the stable index value will be either equal to 2 or too close to 2. If the impact is medium, then the stable index value will the close to 2, and if the impact is high, then the index value will be very far away from 2 or even less than 2. In such cases, one can monitor the event(s) and take decisions that can neutralize the impact. Sometimes the index behaviour gets adjusted as the market conditions changes and in

a few cases, the decisions are taken that can influence the market can change the behaviour to normal.

Adding this step to the analysis will help the practitioners to take appropriate decisions on the stocks.

Conclusion

The study is aimed at understanding the behaviour of the NIFTY sectoral indices and has three objectives. The first objective is to study the tail behaviour of each of the index variables, the second is to identify the extreme value distribution, and the third is to estimate the stable index and study the cumulative index variable. The data required for the study was collected from the NSE website and the analysis was carried out every year from 2010 to 2022. Appropriate estimation methods were used to calculate the required quantities. From the results of the data analysis, we conclude that most of the indices do not satisfy the assumption of normality and are heavy-tailed. Also, though the indices do not satisfy the assumption of normality, the cumulative index variable follows most of the time the normal pattern and a few occasions stable. Through this study, we propose a framework that will help the practitioners while analyzing the stock market data. Through this study, after observing the NIFY indices behaviour, we suggest the practitioners follow the sequence given while deciding on the NIFTY sectoral indices. A similar flow can be given after studying other indices. From our analysis, we conclude that the behaviour of the extremes is Weibull and Fréchet. We finally conclude that the cumulative sectoral index variables follow a normal model for almost all the sectors for many years. That is, the sectors could sustain the shocks generated by the critical events during the given time horizon.

Limitations and Future Work

As in any study, the current study also has few limitations, and the following gives the same

a. We have considered only the indices and not the individual stocks under each of the sectoral indices. One can consider the individual stocks under each sector and study the movement of the index values with the simultaneous movements in the corresponding stocks. This will help one to understand the sectoral indices better.

b. We have considered the sectors separately and not as combinations. One can consider the related sectors and apply multivariate estimation methods to understand the sectoral indices better. Also, appropriate predictive models can be built to understand the sectoral index's future behaviour.

c. We haven't considered time series models to understand the behaviour of the sectoral indices. One can consider these models to understand the movements of the sectoral indices better. In this case, we use the sample path properties of each of the indexes and classify them appropriately.

d. We haven't considered specific events related to each of the sectors and studied their behaviour in association with these events. One can do the same and identify the events that impact the behaviour significantly. This will be interesting and also help the decision-makers to appropriately take decisions on the events and decrease their impact.

e. One can also build predictive models based on the results obtained in the current study and use the same for understanding future outcomes.

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