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Value at Risk Estimation for the BRICS Countries: A Comparative Study

Ameni Ben Salem¹, Imene Safer² and Islem Khefacha³

Abstract

This paper aims to investigate some statistical methods to estimate the value-at-Risk (VaR) for stock returns in the BRICS countries from 2011 to 2018. Four different risk methods are used to estimate VaR: Historical Simulation (HS), Risk metrics, Historical Method and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Process. By applying the Backtesting technique, we test the effectiveness of these different methods by comparing the calculated VaR with the actual realized losses (or gains) of the portfolio or the index. The results show that for the all-BRICS countries and at different confidence levels, the Historical Method and the Historical Simulation are the appropriate methods, while the GARCH model failed to predict precisely the VaR for all BRICS countries.

Keywords: Value-at-Risk, BRICS, Risk metrics, Historical Simulation, GARCH, Historical Method, Backtesting, Confidence level.

JEL Classification: C01; C58; D84; G00; G17

1. Introduction

The quantification, forecasting and management of market risks are major concerns for financial institutions. This is because exposure to extreme price fluctuations in financial markets can lead to sudden and significant losses. Therefore, managers and researchers are responsible for ensuring financial

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stability. So, they should rely on an extensive database and metrics tables to correctly identify potential risks.

In recent years, many concepts of risk measurement have been developed. The main risk management methodology is the Value-at-Risk VaR method, which combines with other risk minimization techniques to achieve optimal results. VaR is the largest portfolio loss we can expect over a given period with a certain level of confidence. This value is a simple and easily understandable number which presents the risk to which the institution is exposed in the financial market. Despite its simple implementation, VaR has been the subject of several criticisms (Artzner et al., 1999, Yamai et Yoshiba, 2002, 2005, Sobreira et al. 2020).

In this research, we will compare the performance of different VaR estimation techniques for the BRICS countries (Brazil, Russia, India, China, and South Africa) from 2011 to 2018. We underline that this Research compares VaR based on the stock returns of the market indexes. Choosing an appropriate measure of VaR that gives an accurate estimate is an essential but a challenging task. In this study, VaR is estimated using four different risk methods: Historical Simulation (HS), Risk Metrics, Historical Method and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) process.

Our objective through this research is to improve the existing literature that deals with risk management by measuring VaR. Indeed, many research studies have studied the performance of these different methods, particularly in the context of BRICS countries. However, the goal of this research is to test the reliability of the different methods to retain the best methods which estimate the VaR. VaR's results will be evaluated with backtesting and compared using a loss function approach.

Based on the previously mentioned objectives, the problem that can be outlined is: What is the most reliable method for estimating VaR and to what extent do changes in data and confidence level influence performance and reliability value-at-risk (VaR) measures in BRICS countries?

2. VaR Estimation Method

VaR is a measure of the risk of loss of investments. It estimates how much a set of investments could lose (with a given probability), under some market conditions, over a defined period such as a day. Businesses and financial sector regulators use VaR to assess the amount of assets needed to cover potential losses (Bonga-Bonga and Nleya, 2016). This definition accepted by all financial investors is as follows: “VaR is the maximum potential loss that a portfolio can suffer, for a given time horizon and a given level of probability, assuming that this portfolio remains unchanged for the specified horizon”. Manganelli and al. (2001)

Bayer (2018) argues that although it is difficult, it is crucial to choose between alternative modelling and value-at-risk (VaR) forecasting strategies. An improperly selected risk model can have dramatic effects on portfolios and the market, as evidenced by the stock market crash of 2015 when many standard approaches predicted insufficiently low levels of risk.

Choosing an appropriate VaR estimation method is an important but difficult task. Indeed, Hendricks (1996) suggested that further research aimed at comparing and combining the best features of the approaches examined might be useful. For this, it seems necessary to us to compare the different estimation methods of VaR, namely Risk Metrics, Historical Simulation, Historical Method, and Variance-Covariance Method, under the GARCH name.

2.1 Historical Simulation

Some researchers, such as Jawwad and Palgrave (2014), explain that Historical Simulation (HS) is the most popular and efficient method. The characteristics of the HS method:

- Relatively simple to set up
- Does not assume any form of distribution.
- Depends on the quality and availability of data.

According to Gajadharsingh (2013): “The empirical quantile method (or Historical Simulation) is a straightforward method of estimating risk measures. It is based on the empirical distribution of historical data on the returns of a financial portfolio. Formally, VaR is estimated simply by directly reading the empirical studies of past returns”.

Wiener (1999) asserts that historical simulation belongs to the nonparametric method of calculating VaR. What is common to all nonparametric approaches is the empirical distribution, obtained from the observed data, as opposed to the parametric approach (where assumptions about the theoretical distributions of return are used). The main feature of historical simulation is its ease of implementation.

The Historical Simulation allows us to estimate the VaR of a portfolio by considering the amount invested in the portfolio in general and in each of its securities.

2.2 Historical Method

After identifying the significant risk factors for a financial market, we use the historical data collected to deduce the amount of loss. According to Didier (2014): "The historical method requires knowing the price history for an index to calculate the change in its value over time. This method is very inexpensive in terms of calculation and technique. In addition, no prior assumption on the form of the distribution is required. "

This method can determine a market index's daily Profits and Losses (P&L) which is then ranked in ascending order. Depending on the number of P&L calculated and the desired confidence interval, the historical VaR equals to the corresponding P&L value.

This simplicity of implementation generates many limits. While among its drawbacks, this method is unsuitable for derivative products (options, warrants, futures contracts, etc.). In addition, historical data must be sufficiently and widely large compared to the horizon of the VaR and its confidence level but not too much to ensure that the law of probability has not changed too much over the given period.

2.3 Risk Metrics

Risk Metrics was introduced in 1994. It contains datasets and techniques used to calculate the value at risk (VaR) of a portfolio of stocks or a market index. Morgan and Reuters collaborated in 1996 to develop the methodology and make the data widely available to practitioners, managers, and researchers. The objective is to improve and promote the transparency of market risks and

subsequently create a benchmark for risk measurement by providing advice to clients on managing market risks.

Morgan calculates the VaR as the conditional variance as a weighted average shifted by one period and squared logarithms at period t-1 (Sobreira and Louro 2020):

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1 - \lambda) r_{t-1}^2 \quad (1)$$

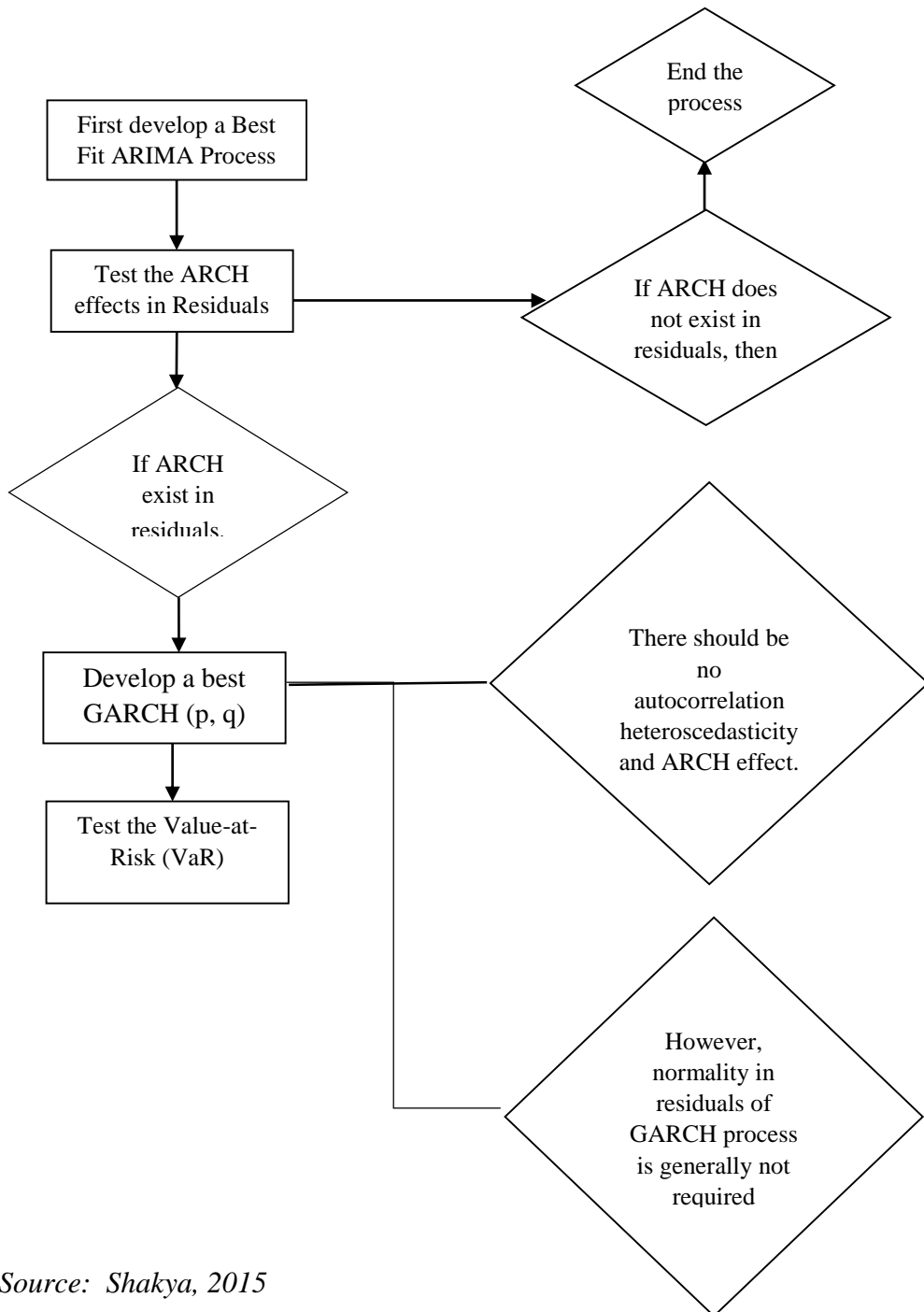
σ_t^2 : The conditional variance; r_t^2 : Square yield

Usually, $\lambda = 0.94$ for the forecast of daily volatility.

2.4 Generalized autoregressive conditional heteroscedasticity process (GARCH)

In 1982, Engle presented in his famous research paper entitled "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation" the family of conditional autoregressive heteroskedastic (ARCH) models. Since then, other research has focused on the modelling of conditional volatility, such as the work of Bollerslev, Chou and Kroner (1992), Bollerslev, Engle and Nelson (1994) and Diebold and Lopez (1995). Other papers have compared specific models for predicting conditional volatility, such as West and Cho (1994) and Heynen and Kat (1993).

Figure 1: The steps for calculating the VaR by the GARCH method



Source: Shakya, 2015

According to Angelidisa et al. (2004), the GARCH (p, q) model successfully captures several features of financial time series, such as thick-tailed returns and volatility clustering, as noted by Mandelbrot (1963) "... big changes tend to be followed by big changes in one or the other of the signs, and small changes tend to be followed by small changes...". On the other hand, the GARCH structure presents some drawbacks of implementation since the variance depends only on the magnitude and not on the sign ε_t , which is in contradiction with the empirical behavior of stock prices where a leverage effect may be present. This term, introduced by Black (1976), refers to the tendency of changes in stock returns to be negatively correlated with changes in return volatility, so that volatility tends to increase in response to bad news, ($\varepsilon_t < 0$) and decrease in response to good news ($\varepsilon_t > 0$). Additionally, Brooks and Persaud (2003) state that a VaR model that ignores asymmetries in the volatility specification is most likely to generate inaccurate predictions.

3. Backtesting

3.1 Definition

Considering the existence and the great diversity of methods for providing the VaR's estimation, many studies propose that different models applied for the same research generally led to very different estimates of VaR and therefore the risk for the same portfolio or the same market index.

Risk Managers need to assess VaR forecasts outside the regulatory standards imposed by Basel II by setting up Backtesting procedures (Silver et al., 2020).

Backtesting is a set of statistical procedures used in financial institutions to designate the testing of a strategy of a predictive model from existing historical data to verify that the actual losses observed are in line with the expected losses. This involves systematically comparing the historical VaR forecasts with the observed returns of the portfolio (Jorion, 2007).

This kind of simulation makes it possible to refine a model and verify hypotheses. Backtesting requires real historical data. According to Niepolla (2009): "The results of the Backtests provide an indication of potential problems within the system. A severe underestimation of risk is discovered, especially for stocks and stock options. However, the turbulent market

environment poses challenges in evaluating backtesting results, as VaR models are only known to be accurate under normal market conditions”.

However, such a Backtest involves some verification risks. First, we know that data from the past is not necessarily a guide to future performance. It is therefore desirable to keep realistic and simple assumptions. Over-optimizing a backtest would not lead to optimizing a strategy but to optimizing the past so that the strategy is always the best.

Backtesting must therefore make it possible to determine the most appropriate method (or methods) (Historical Simulation, Historical Method, Risk Metrics, GARCH) to predict the VaR. We must distinguish between the forecast validation test and the comparison test of forecasts, such as the Kupiec TUFF test, the Kupiec POF test or the Christoffersen independence test.

Only large institutions and professional fund managers use Backtesting because of the expense of obtaining and using detailed data sets. However, backtrading is used on a large basis and independent backtesting platforms. Although the technique is widely used, it has weaknesses.

3.2 Backtesting Value at Risk Forecast: Kupiec Pof-Test

The POF (proportion of failure) test examines whether the number of exceptions meets the given confidence level. The null hypothesis of failure is expressed as follows:

$$H_0: p = \hat{p} = \frac{x}{T} * 100 \quad (2)$$

Where:

p : Percentage of failure

\hat{p} : The observed failure rates

x : Number of exceptions

T : Number of total observations

Once the one-day VaR and the number of exceptions for each confidence level are known, the likelihood ratio test must be calculated.

If the calculated LR exceeds the critical value, the null hypothesis and the accuracy of the model must be rejected for a certain level of confidence.

The “LR” likelihood ratio test is expressed according to the following expression:

$$LR\ POF = -2 \ln \frac{((1-p)^{T-x} * p^x)}{\left[1 - \left(\frac{x}{T}\right)\right]^{T-x} * \left(\frac{x}{T}\right)^x} \quad (3)$$

Where:

p : Confidence level

T : Total number of observations

x : Number of exceptions

4. Empirical Analysis

When we seek to invest in the stock market, we tend to focus on the developed markets of the European Union or the United States and we forget the emerging countries, namely the countries of the BRICS group, which are distinguished by their vast growing economies. Indeed, the BRICS countries attract a large part of capital inflows and represent a destination of choice for the investments of many global portfolio managers. The main problem with stock markets in developing countries is the access to markets and financial information. Unless investors know emerging markets like the back of their hand, they are therefore discouraged from investing in BRICS markets individually. They should therefore ask for funds and apply risk measurement methods based on historical data to build a complete idea of the market.

4.1 Empirical Results

4.1.1 Historical Simulation

The data used for the statistical calculations come from a secondary source, specifically, the share prices of 20 companies with the largest market capitalizations (see Annex 1) for a period of 2085 days. The data was collected via the “Datastream” financial and macroeconomic data platform. First, we assumed we have \$ 2000 to invest in a portfolio at the rate of \$ 100 for each company. Thus, daily returns are calculated for each company and then the daily return of the portfolio is calculated so that the daily returns of twenty companies are added up.

The third step is to calculate the overnight VaR for the portfolio at the confidence levels of 95% and 99%, respectively using the formula (percentile) in excel:

$$\text{Var (99\%)} = \text{CENTILE (n1: nt; 99\%)} \quad (4)$$

The daily losses are then considered to compare these values with the estimated calculation of the VaR. If the value of the portfolio loss is greater than the predicted overnight VaR value, then the exception exists. This comparison is necessary to see how many exceptions occur at the 95% and 99% confidence levels. (Annex 2)

Table 1: VaR estimation by the HS Method (Historical Simulation)

Countries	Confidence level	VaR%	Number of exceptions	Number of total observations
Brazil	95% ($\alpha=5\%$)	-46,5514749	103	2085
	99% ($\alpha=1\%$)	-74,7337198	19	2085
Russia	95% ($\alpha=5\%$)	-38,10863374	109	2085
	99% ($\alpha=1\%$)	-61,97126617	32	2085
India	95% ($\alpha=5\%$)	-32,8803826	94	2085
	99% ($\alpha=1\%$)	-49,2278663	23	2085
China	95% ($\alpha=5\%$)	-44,29199755	95	2085
	99% ($\alpha=1\%$)	-74,22332947	29	2085
South Africa	95% ($\alpha=5\%$)	-35,38409499	122	2085
	99% ($\alpha=1\%$)	-61,00736923	20	2085

Source: Survey Data, 2022

The table shows the estimated VaR for the BRICS group at the 99% and 95% thresholds, as well as the number of exceptions (losses that have exceeded the VaR) and the number of total observations.

The highest number of exceptions is recorded in South Africa at the 95%. This means that following the estimation of the VaR by the HS, 122 values exceeded the worst expected loss in Brazil at the threshold by 95%, while there are only 20 losses that have exceeded the VaR at 99% threshold.

Generally, and depending on the results obtained, the VaR estimated at 99% is lower than that at 95% since the confidence level will be more limited (there is only a 1% chance that the losses will exceed the value at risk). And even for

the number of exceptions (losses that exceeded VaR at 99% are therefore less than that at 95%).

4.1.2 The Historical Method

We carry out our analysis based on the repatriation of the daily closing values over the last 8 years (from 2011 to 2018) of the BRICS group market indices (BOVESPA, RTS, SENSEX, SSE, JSE). The data was extracted from the financial data platform "FactSet". We thus calculate the daily earnings, which are sorted by increasing value. The confidence level is then calculated from the number of observations (number of the day) according to the following expressions:

$$\text{VaR reference} = (\text{N}^\circ \text{ line} / \text{Total number of lines}) \quad (5)$$

$$\text{Var at } x\% = (100 - \text{Ref VaR})$$

The risk value is then obtained at the 99% and 95% levels by calculating the sorted gains. (Annex 3)

The daily losses are then considered to compare these values with the estimated calculation of the VaR. If the negative return (loss) of the index is greater than the expected overnight VaR value, the exception exists. This comparison is necessary to see how many exceptions occur at 95% and 99% confidence levels.

Table 2 presents the estimated VaR for each country of the BRICS group at the 99% and 95% thresholds. The number of exceptions (losses that exceed the VaR) and the number of total observations are different from each country due to national holidays and missing data for some indices.

The VaR for Brazil at 95% is equal to -1317 and -2017 at 99%, meaning that there is a 5% chance that the loss will exceed -1317 and a 1% chance that the loss will exceed -2017.

Table 2: VaR estimation by the Historical Method

Countries	Confidence level	VaR	VaR en % =	Number of exceptions	Number of total observations
Brazil	95% ($\alpha=5\%$)	-1317	1.62	98	1977
	99% ($\alpha=1\%$)	-2017	2.25%	19	1977
Russia	95% ($\alpha=5\%$)	-32,93	3.11%	99	2000
	99% ($\alpha=1\%$)	-62,87	5.44%	19	2000
India	95% ($\alpha=5\%$)	-351,28	0.94%	98	1972
	99% ($\alpha=1\%$)	-590,05	1.62%	19	1972
China	95% ($\alpha=5\%$)	-58,167	2.11%	96	1945
	99% ($\alpha=1\%$)	-175,56	6.58%	18	1945
South Africa	95% ($\alpha=5\%$)	-680,96	1.32%	103	2085
	99% ($\alpha=1\%$)	-1161,52	2.52%	20	2085

Source: Survey Data, 2022

The number of exceptions in the five countries is almost equal. On average, 19 Return (loss) values exceed the VaR at 99% for all countries. One hundred stocks were the exception at the level 95% threshold. This means that the measure of VaR by the Historical Method is robust and gives the exact estimates for all countries (it is no longer affected by the database).

4.1.3 Risk Metrics

As the "Historical Method" technique, we use the same database to calculate the daily returns of the market index for each country according to the following expression:

$$R_t = \ln(P_{C_t}/P_{C_{t-1}}) \quad (6)$$

Where:

R_t : Daily returns

P_{C_t} : The closing price at time t.

$P_{C_{t-1}}$: The closing price at time t-1.

We then calculate the variance and the standard deviation to estimate the VaR at levels 95% and 99% by the following expression (See *Annex 4*):

$$VaR(1 - \alpha) = \sigma_t * NORMAL.STANDARD.INVERSE.LAW.N(\alpha) \quad (7)$$

Table 3: VaR estimation by Risk Metrics

Countries	Confidence level	VaR	Number of exceptions	Number of total observations
Brazil	95% ($\alpha=5\%$)	-2,388%	92	1977
	99% ($\alpha=1\%$)	-3,378%	20	1977
Russia	95% ($\alpha=5\%$)	-2,956%	83	2000
	99% ($\alpha=1\%$)	-4,181%	32	2000
India	95% ($\alpha=5\%$)	-1,576%	98	1972
	99% ($\alpha=1\%$)	-2,229%	30	1972
China	95% ($\alpha=5\%$)	-2,268%	82	1945
	99% ($\alpha=1\%$)	-3,208%	40	1945
South Africa	95% ($\alpha=5\%$)	-1,680%	103	2085
	99% ($\alpha=1\%$)	-2,376%	36	2085

Source: Survey Data, 2022

Table 3 shows the estimated VaRs for each country of the BRICS group at the levels of 99% and 95%, as well as the number of exceptions. The worst loss recorded by the Risk Metrics method is that of the Russian (-4.181%) at the 99% threshold. Among the 2000 observations, 32 performance values (losses) exceed the VaR.

4.1.4 GARCH

We describe in the following the different steps of the application of the GARCH method to estimate the VaR.

Step 1: download the data.

We download the adjusted closing prices of market indices from January 1, 2011, to December 31, 2018, using Yahoo Finance. Since we have missing data, we use the `na.omit` command. This function removes all incomplete cases from the data (see *Annex 5*).

Step 2: Obtain data returns

Based on the daily returns, we can conclude that high volatility days are followed by high volatility days and low volatility days by low volatility days (See *Annex 6*).

Step 3: Find the best model using ARIMA

In this step, it is a question of finding the best ARIMA model (p, d, q) based on the Bayesian information criteria. Note that the returns of a financial series are always stationary and therefore integrated of order 0 I (0). Therefore, ARIMA is in fact only an ARMA (p, q) process (See *Annex 7*).

Step 4: Testing the ARCH effect

To validate the ARIMA-type modelling, it is necessary to test the absence of heteroskedasticity through the ARCH effect. To do this, it is a question of applying the Ljung-Box test on the first 12 shifts of the squared residuals of the best ARIMA model under the null hypothesis of no ARCH effect. (See *Annex 7*)

If the value of p of the Ljung-Box test is less than 5% of significance, the ARCH effect is indeed present and the modulization of the GARCH type is then essential (See *Annex 7*).

Step 5: Development of a GARCH model

For the sake of simplicity, we apply a GARCH (0,1) type modelling. For the GARCH theory, we specify the object called `res_garch01_spec`, in which we want to develop a GARCH (p, q) on ARIMA (p, 0, q).

Step 6: Backtesting the risk model

Once the GARCH model has been estimated, we verify the performance of the model by performing a historical backtest. To do this, we can compare the estimated VaR (value at risk) with the actual return over the period. If the return is more negative than the VaR, we have exceeded the VaR. In our case, exceeding the VaR should only occur 1% of the time if we have specified a confidence level of 99%, and 5% of the cases if we have specified a confidence level of 95%. The 1% and 5% VaR show the 1% and 5% probability of its extreme loss. (See *Annex8*)

Table 4 shows the number of exceptions and the total number of observations, which differ between countries due to missing data.

The GARCH method records very high numbers of exceptions for the 5 countries, a sign of an inaccuracy in the estimate of the VaR by this method.

Table 4: estimation VaR by the GARCH model

Pays	Confidence level	Number of exceptions	Number of total observations
Brazil	95% ($\alpha=5\%$)	115	1854
	99% ($\alpha=1\%$)	32	1854
Russia	95% ($\alpha=5\%$)	84	1310
	99% ($\alpha=1\%$)	20	1310
India	95% ($\alpha=5\%$)	149	1840
	99% ($\alpha=1\%$)	72	1840
China	95% ($\alpha=5\%$)	101	1824
	99% ($\alpha=1\%$)	49	1824
South Africa	95% ($\alpha=5\%$)	140	1965
	99% ($\alpha=1\%$)	50	1965

Source: Survey Data, 2022

4.2 Backtesting Value at Risk Forecast: Kupiec Pof-Test

Table 5: Percentages of exceptions: A comparative result

	95%				99%			
	HS	Historical Method	Risk metrics	GARCH	HS	Historical Method	Risk metrics	GARCH
Brazil	4.94%	4,957%	4.65%	6,2%	0.91%	0,961%	1.01%	3.6%
Russia	5.32%	4,950%	4.15%	6.4%	1.53%	0,950%	1.6%	1.5%
India	4.51%	4,970%	4.96%	8.1%	1.10%	0,963%	1.52%	3.9%
China	4.56%	4,936%	4.21%	5.5%	1.39%	0,925%	2.05%	2.7%
South Africa	5.85%	4,938%	4.94%	7.1%	0.96%	0,959%	1.72%	2.5%

Source: Survey Data, 2022

The percentages indicated in the table reflect the percentages of rejections of the null hypothesis. For the more liberal level of coverage ($\alpha = 5\%$), GARCH has the worst performance for most countries, while HS fails in Russia and South Africa. In addition, Risk Metrics dominate the three other methods. When a more conservative level of coverage is considered ($\alpha = 1\%$), the historical method has shown the best overall performance, more clearly

outperforming GARCH and Risk Metrics. In general, we get a higher percentage of VaR method for more liberal coverage levels.

Once the one-day VaR and the number of exceptions for each confidence level are known, the likelihood ratio test must be calculated.

If the calculated LR exceeds the critical value, the null hypothesis and the model accuracy must be rejected for a certain level of confidence.

The null hypothesis indicates that the observed failure percentage equals the failure rate, which is suggested by the confidence interval. Moreover, the purpose of accepting the null hypothesis is to prove that the model is accurate. In the case where the quantity of likelihood ratio is greater than the critical value of χ^2 , the conclusion on the rejection of the null hypothesis and the inaccuracy of the model would be made.

The “LR” likelihood ratio test is expressed according to the following formula:

$$LR\ POF = -2 \ln \frac{((1-p)^{T-x} * p^x)}{\left[1 - \left(\frac{x}{T}\right)\right]^{T-x} * \left(\frac{x}{T}\right)^x} \quad (8)$$

Where:

p : Confidence level

T : Total number of observations

x : Number of exceptions

According to Jorion (2001), “the likelihood ratio is a statistical test that calculates the ratio between the maximum probabilities of a result under two alternative hypotheses. The maximum probability of the result observed under the null hypothesis is defined in the numerator and the maximum probability of the result observed under the alternative hypothesis is defined in the denominator. The decision is then based on the value of this ratio. The smaller the ratio, the larger the LR statistic will be. If the value becomes too large and greater than the critical value of the chi-square distribution, the null hypothesis is rejected. According to statistical decision theory, the likelihood ratio test is the most powerful test in its class”.

As we have already specified for the POF test, the calculation of the likelihood test is necessary. Thus, it can be calculated by plugging the appropriate data from the table (1,2,3 and 4) into the likelihood ratio formula. This means that

strong evidence is needed to reject the null hypothesis and the accuracy of the model. To draw a valid conclusion about the validity of the model, the critical value at the two levels 5% and 1% are determined from the chi-square table; the two values are 3.84 at level 5% and 6.63 at level 1%. (*Annex 9*)

Table 6: Kupiec-POF test results

	95%				99%			
	HS	Risk metrics	Historical Method	GARCH	HS	Risk metrics	Historical Method	GARCH
Brazil	Accepted	Accepted	Accepted	Reject	Accepted	Accepted	Accepted	Reject
Russia	Accepted	Accepted	Accepted	Reject	Accepted	Accepted	Accepted	Accepted
India	Accepted	Accepted	Accepted	Reject	Accepted	Accepted	Accepted	Reject
China	Accepted	Accepted	Accepted	Accepted	Accepted	Reject	Accepted	Reject
South Africa	Accepted	Accepted	Accepted	Reject	Accepted	Reject	Accepted	Reject

Source: Survey Data, 2022

The test used for the Backtesting of the amount of VaR expected in this research is a so-called failure proportion test. This test only considers the number of exceptions, not when the exception occurs. Therefore, the number of exceptions is critical information necessary for the model to be accurate or not (whether the null hypothesis is rejected or accepted).

- If we refer to the historical simulation method and to the historical method, the two methods are reliable for all countries at levels of 95% and 99% thresholds, while the difference lies in the Risk metrics method, which underestimates the risk at levels 99% level for China and South Africa. In comparison, the GARCH method gives a poor estimate for both thresholds and for all countries, except at level 95% for China and at 99% for Russia.
- If we seek to estimate the risk in Brazil and India, we must apply either the historical method or historical simulation or Risk metrics. These methods gave us a satisfactory estimate at levels 99% and 95%.
- The only method that should not be applied for risk measurement in Russia is GARCH.
- The risk estimates for China at level 99% can be applied by the four methods of measuring VaR. While at level 95%, the GARCH method can no longer be used because, according to the POF test, this method is no longer reliable.

- The results obtained from these four methods and after the application of the validation test, the VaR at level 95% must be estimated by the historical method, Risk metrics and by historical simulation, while at level 99%, the estimation is made by historical simulation and by the historical method.

5. Conclusion

The variety of risk measurement approaches that have been developed in the financial market over the last decades raises a question about the validity of these measurements. One of the most popular measures in the literature is the value at risk (VaR). Knowing the accuracy of the measurement is especially important for financial institutions, as they use VaR to estimate the amount of liquidity they need to reserve to cover potential losses. Any disability in the VaR model can mean that the institution does not hold sufficient reserves and could lead to significant losses, not only for the institution but potentially for its depositors and retail investors.

This research implements a VaR analysis for the BRICS countries (Brazil, Russia, India, China, and Africa from South) stock markets with market indices that represent the most relevant stocks in these countries. In addition, different performance measures for the assessment of the estimated VaR were discussed. The objective was to study the reliability of four methods (Historical Simulation, Risk metrics, Historical Method, GARCH) in estimating market VaR.

The use of backtesting is a primary task, which consists in comparing the measure of the calculated VaR with the real losses (or gains) realized by the portfolio by the index. A Backtest is based on the level of confidence assumed in the calculation.

The results showed that in the five countries and at different levels of trust, the Historical Method and Historical Simulation were the most robust. The change of country and threshold has no effect on the reliability of the VaR estimate. This means that there were two methods to estimate risk in emerging BRICS markets. While the GARCH model arrived last, it failed for all countries.

The results were obtained following the Kupiec POF Backtesting, but they can be confirmed by other tests, such as the Kupiec TUFF test (1995), the test of

independence of Christoffersen (1998), DBI of Christoffersen and Pelletier (2004) and the DQ Engle and Manganelli test (2004).

As a future line of research, it would be interesting to apply these methods to the ES (Expected Shortfall), which has become increasingly important in the field of financial market risk measurement. It is an alternative to value at risk, which is more sensitive to the shape of the tail of the loss distribution. In addition, it would be useful to extend our analysis with additional VaR forecasting methods such as Monte Carlo simulation, Parametric Method, and EVT (Extreme Value Theory).

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Appendices:

Annex 1: market portfolios sorted by capitalization

	A	B	C	D	E
1	RUSSIE 20/50	INDE 20/50	CHINE 20/1474	AFRIQUE DE SUD 20/40	BRAZIL 20/50
2	INTER RAO YEES	SUN PHARM.INDUSTRIES	BANK OF COMMS.'A'	NASPERS	VALE ON
3	GAZPROM	TATA CONSULTANCY SVS	BANK OF CHINA 'A'	ASPEN PHMCR.HDG.	ITAU UNIBANCO HOLDING PN
4	MMC NORILSK NICKEL	TATA MOTORS	ALUMINUM CORP.OF CHINA 'A'	LONMIN (JSE)	AMBEV ON
5	AEROFLOT RUSS.AIRL.	TATA STEEL	AIR CHINA LIMITED 'A'	EXXARO RESOURCES	PETROLEO BRASILEIRO ON
6	NK LUKOIL	RELIANCE INDUSTRIES	AN INSURANCE (GP.) CO. OF CHIN	SASOL	BANCO BRADESCO PN
7	FSK YEES	MARUTI SUZUKI INDIA	CITIC SECURITIES 'A'	ANGLOGOLD ASHANTI	BANCO DO BRASIL ON
8	SEVERSTAL	VEDANTA	BAOSHAN IRON & STL.'A'	BIDVEST GROUP	RAIA DROGASIL ON
9	TATNEFT	HDFC BANK	KWEICHOW MOUTAI 'A'	MONDI	ESTACIO PARTICIPACOES ON
10	NOVATEK	HOUSING DEVELOPMENT FINANCE CORPORATION	JIANGXI CPR. 'A'	MTN GROUP	TELEFONICA BRASIL PN
11	URALKALI	BAJAJ FINANCE	EVELOPMENTS AND HOLDINGS GR	HARMONY GOLD MNG.	B3 BRASIL BOISA BALCAO ON
12	POLYUS	LARSEN & TOUBRO	YOUNGOR GROUP 'A'	REINET INVESTMENTS (JSE) SCA	EQUATORIAL ENERGIA ON
13	NOVOLIPETSK STEEL	HERO MOTOCORP	BEIJING GEHUA CATV.NET. 'A'	VODACOM GROUP	BRF BRASIL FOODS ON
14	MOBILE TELESYSTEMS	AXIS BANK	INNER MONGOLIA YILI INDLGP.'A'	FIRSTSTR	GOL LINHAS AEREAS INTELIGENTES PN
15	MECHEL OAO	ASIAN PAINTS	SAIC MOTOR 'A'	KUMBA IRON ORE	QUALICORP ON
16	SURGUTNEFTGAS	MAHINDRA & MAHINDRA	DAQIN RAILWAY 'A'	SHOPRITE	BB SEGURIDADE ON
17	ROSTELECOM	HCL TECHNOLOGIES	SHAI.PUDONG DEV.BK. 'A'	NEDBANK GROUP	GERDAU PN
18	SBERBANK OF RUSSIA	ITC	INDUSTRIAL & COML.BK.OF CHINA 'A'	ANGLO AMERICAN PLATINUM	ITAUSA INVESTIMENTOS ITAU PN
19	PIK GROUP	KOTAK MAHINDRA BANK	OFFS.OIL ENGR. 'A'	IMPALA PLATINUM	LOJAS RENNER ON
20	ROSSETI	INFOSYS	HUANENG POWER INTL.'A'	STANDARD BANK GROUP	LOJAS AMERICANAS PN REP1 PN
21	OC ROSNEFT	HINDUSTAN UNILEVER	CHINA YANGTZE PWR. 'A'	STEINHOFF INTL.HOLDING	RUMO ON

Annex 2: Calculation of VaR by Historical Simulation

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	
4															
5	#	DATE	NASPERS	ASPEN PHMCR.HDGL.	LOMIN (JSE)	EXXARO RESOURCES	SASOL	ANGLOGOLD ASHANTI	BIDVEST GROUP	MONDI	MTN GROUP	HARMONY GOLD MNG.	REINET INVESTMENTS (JSE) SCA	VODACOM GROUP	FIRS
6	1	15/12/2018	2811,84	134,82	8,59	137,87	425	181,75	206,85	309,57	89	25,2	218,45	132	
7	2	28/12/2018	2811,84	133,31	8,06	131,46	426,74	180,84	204	306,5	88,06	24,94	217,78	131,6	
8	3	27/12/2018	2779,55	130	8,19	132,15	419,85	182,7	197,63	302,44	87,79	25,03	207,47	128,42	
9	4	26/12/2018	2866,43	129,5	7,9	134,07	422	184	203,16	309	85,5	24,8	211	127,78	
10	5	25/12/2018	2866,43	129,5	7,9	134,07	422	184	203,16	309	85,5	24,8	211	127,78	
11	6	24/12/2018	2866,43	129,5	7,9	134,07	422	184	203,16	309	85,5	24,8	211	127,78	
12	7	21/12/2018	2792,45	129,72	7,9	132,5	411,32	176,22	201,85	301,87	83,68	24,22	204,08	129,08	
13	8	20/12/2018	2717,27	133,29	7,92	134,65	412,4	179,9	203,97	301,88	84,78	25,06,7	207,7	127,82	
14	9	19/12/2018	2734,27	133,17	8,73	134,31	417,16	179,47	203,91	298,79	85,7	25,9	207,48	130,62	
15	10	18/12/2018	2737,69	134,38	8,97	139,2	407,91	175,99	198,5	296,24	84,13	23,96	213,6	123,9	
16	11	17/12/2018	2732,59	129,5	8,96	138,58	428,63	170,82	205,22	300,09	86,01	22,81	216,44	124,3	
17	12	14/12/2018	2732,59	129,5	8,96	138,58	428,63	170,82	205,22	300,09	86,01	22,81	216,44	124,3	
18	13	13/12/2018	2734,28	141,64	8,59	138,46	426,94	170,78	204,5	300,14	84,95	23,27	217,1	124,49	
19	14	12/12/2018	2770,29	142,76	8,52	129,3	424,07	187,36	198,83	309,5	85,94	23,29	220,95	125,7	
20	15	11/12/2018	2764,44	142,04	8,62	127,63	423,56	164,5	193,02	305,26	83,62	22,85	226,14	123,51	
21	16	10/12/2018	2666,4	138,32	8,59	125,88	413,69	161,54	193,22	301,79	83,89	23,62	215,6	120	
22	17	07/12/2018	2738,43	144,58	8,4	128,19	431,44	155,42	199,49	299,06	86,39	23,13	212,21	123,16	
23	18	06/12/2018	2671,25	145,73	8,45	129,46	425,5	153,95	201,5	306,05	86	22,99	213,13	122,66	
24	19	05/12/2018	2785,29	149,9	8,26	132	431,5	147,46	209,95	310,5	85,85	22	207,23	125,17	
25	20	04/12/2018	2840,93	148,4	8,09	131,97	431,36	144,4	205,5	310	86,74	21,19	205,03	125,83	
26	21	03/12/2018	2800,7	146,5	7,95	132	434	139,66	202,57	314	87,22	21	203,58	125,78	
27	22	02/12/2018	2679	147,08	7,86	129,19	406,28	139,13	203,3	305	87,38	20,87	202,19	125,5	
28	23	29/11/2018	2734,27	151,11	8,1	132,5	421,07	140,51	209,35	312,01	89,8	21,6	210	128,26	
29	24	28/11/2018	2806,94	149,77	8,01	132,08	420,24	139,45	203,3	313,72	88,4	21,8	213,82	123,9	
30	25	27/11/2018	2705,18	150,07	8,13	135	412,87	139,53	199,31	313,21	88,14	21,75	210,34	124,1	
31	26	16/11/2018	2736,92	150,01	8,07	143,8	415,43	141,8	200,79	316,62	89,77	23,98	216,3	125,1	

	A	B	C	D	E	F	G	H	I	J	K	L	M	N								
3																						
4																						
5	NASPERS	EN PHMCR.H	LOMIN (JSE)	EXXARO RESOUR	SASOL	OGOLD ASHVEST	GRO	MONDI	MTN GROUP	PANONY GOLD	INVESTMENTS	DACOM	GRC	FIRSTRAND	MBA IRON	C	SHOPRITE	NEDBANK GROUP	IGLO AMERICAN	PLATINU	IMPAL	
6	0,00%	1,13%	0,01%	3,25%	-0,41%	0,50%	1,39%	1,00%	1,06%	1,04%	0,31%	0,30%	0,44%	1,88%	0,29%							
7	1,18%	2,51%	1,60%	0,99%	1,65%	-1,02%	3,17%	1,33%	0,31%	0,36%	1,85%	2,45%	1,64%	3,44%	0,33%							
8	-3,08%	0,39%	3,61%	-1,44%	-0,51%	-0,71%	-2,76%	-2,15%	2,64%	0,92%	-1,69%	0,50%	0,94%	-1,09%	1,18%							
9	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%	0,00%	0,00%							
10	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%	0,00%	0,00%							
11	2,61%	-0,17%	0,00%	1,18%	2,56%	4,32%	0,65%	2,33%	2,15%	2,37%	3,33%	-1,01%	0,73%	1,80%	2,06%							
12	2,73%	-1,96%	-0,25%	-1,61%	-0,26%	-2,07%	-1,73%	-0,04%	-1,31%	-3,41%	-1,28%	1,22%	-1,40%	-1,27%	1,17%							
13	-0,62%	-0,86%	-9,74%	0,25%	-1,15%	0,24%	0,71%	1,06%	-1,08%	-3,30%	-2,38%	-2,40%	0,45%	0,37%	-3,15%							
14	-0,12%	-1,01%	-2,12%	-3,58%	-2,20%	5,16%	-2,59%	0,85%	1,85%	2,75%	-2,91%	-2,38%	-2,38%	-2,17%	0,23%							
15	0,19%	3,85%	0,11%	0,45%	-4,95%	2,98%	-3,33%	-1,39%	-2,21%	-4,92%	-1,32%	-0,32%	-2,45%	2,40%	-2,26%							
16	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%	0,00%	0,00%							
17	-0,06%	-8,96%	4,22%	0,09%	0,40%	0,02%	0,35%	-0,02%	1,24%	-2,00%	-0,30%	-0,15%	-1,84%	-1,23%	-0,75%							
18	-1,31%	-0,79%	0,82%	6,84%	0,67%	2,02%	2,81%	-1,07%	-1,16%	0,17%	-1,76%	0,64%	-0,17%	2,38%	2,20%							
19	0,21%	0,51%	-1,17%	1,30%	0,12%	1,72%	2,97%	1,38%	2,74%	1,65%	-2,32%	0,15%	1,86%	-0,49%	3,94%							
20	3,61%	2,85%	0,35%	1,38%	2,36%	1,62%	-1,01%	1,14%	-0,32%	-3,31%	4,77%	2,88%	0,93%	-0,03%	-0,93%							
21	-2,20%	-4,41%	-2,12%	-3,58%	-2,20%	5,16%	-2,59%	0,85%	1,85%	2,75%	-2,91%	-2,38%	-2,38%	-2,17%	0,23%							
22	2,12%	-1,50%	1,76%	-0,99%	-1,39%	-0,94%	-0,80%	-2,31%	0,45%	0,53%	-0,43%	0,41%	0,23%	4,67%	-1,02%							
23	-4,18%	-2,14%	2,27%	-1,94%	-1,40%	4,31%	-4,11%	-1,44%	0,17%	4,40%	2,81%	-0,03%	-3,05%	-0,20%	-2,07%							
24	-1,98%	1,01%	2,08%	0,02%	0,03%	2,10%	1,66%	0,16%	-1,03%	3,75%	1,07%	-0,54%	-1,62%	3,48%	-1,47%							
25	1,43%	1,29%	1,75%	-0,02%	-0,61%	3,34%	1,92%	-1,28%	-0,55%	0,90%	0,71%	0,06%	-0,50%	-1,11%	0,56%							
26	4,44%	-0,40%	1,14%	2,15%	6,60%	0,38%	-1,34%	2,91%	-0,18%	0,62%	0,69%	0,22%	2,82%	2,88%	-0,20%							
27	-2,04%	-2,70%	-3,01%	-2,53%	-3,58%	-0,99%	-1,95%	-2,27%	-2,73%	-3,44%	-3,79%	-2,17%	-4,78%	-2,96%	-1,68%							
28	-2,61%	0,89%	1,12%	0,32%	0,20%	0,76%	2,93%	-0,55%	1,57%	1,59%	-1,80%	3,45%	1,40%	-1,94%	0,04%							
29	-0,68%	-0,29%	-1,49%	-0,14%	1,83%	-0,06%	1,98%	0,16%	0,29%	-2,78%	1,64%	-0,66%	0,13%	-0,93%	-0,29%							

• Russia

	A	B	C	D	E	F	G	H	I	J
1	N°	date	RTS (TC)	returns	residuals	returns squa	variance	standard deviation	95%	99%
2	1	01/11/11	1802,23							
3	2	01/12/11	1868,94	3,63%		0,1321%	0,032%	1,797%	-2,956%	-4,181%
4	3	01/13/11	1878,14	0,49%		0,0024%				
5	4	01/14/11	1870,09	-0,43%		0,0018%				
6	5	01/17/11	1901,61	1,67%		0,0279%				
7	6	01/18/11	1900,94	-0,04%		0,0000%				
8	7	01/19/11	1902,75	0,10%		0,0001%				
9	8	01/20/11	1868,46	-1,82%		0,0331%				
10	9	01/21/11	1884,76	0,87%		0,0075%				
11	10	01/24/11	1861,66	-1,23%		0,0152%				
12	11	01/25/11	1863,33	0,09%		0,0001%				
13	12	01/26/11	1894,2	1,64%		0,0270%				
14	13	01/27/11	1911,48	0,91%		0,0082%				
15	14	01/28/11	1885,53	-1,37%		0,0187%				
16	15	01/31/11	1870,31	-0,81%		0,0066%				
17	16	02/01/11	1910,01	2,10%		0,0441%				
18	17	02/02/11	1931,38	1,11%		0,0124%				
19	18	02/03/11	1917,07	-0,74%		0,0055%				
20	19	02/04/11	1928,58	0,60%		0,0036%				
21	20	02/07/11	1935,15	0,34%		0,0012%				
22	21	02/08/11	1910,5	-1,28%		0,0164%				
23	22	02/09/11	1900,28	-0,54%		0,0029%				
24	23	02/10/11	1846,92	-2,85%		0,0811%				
25	24	02/11/11	1881,9	1,88%		0,0352%				
26	25	02/14/11	1879,56	-0,12%		0,0002%				
27	26	02/15/11	1865,99	-0,72%		0,0053%				

• India

	A	B	C	D	E	F	G	H	I	J
1	N°	Date	sensex(TC)	returns	Résiduaux	returns square	variance	standard deviation	95%	99%
2	1	01/03/11	20561,05							
3	2	01/04/11	20498,72	-0,30%		0,0009%	0,009%	0,958%	-1,576%	-2,229%
4	3	01/05/11	20301,1	-0,97%		0,0094%				
5	4	01/06/11	20184,74	-0,57%		0,0033%				
6	5	01/07/11	19691,81	-2,47%		0,0611%				
7	6	01/10/11	19224,12	-2,40%		0,0578%				
8	7	01/11/11	19196,34	-0,14%		0,0002%				
9	8	01/12/11	19534,1	1,74%		0,0304%				
10	9	01/13/11	19182,82	-1,81%		0,0329%				
11	10	01/14/11	18860,44	-1,69%		0,0287%				
12	11	01/17/11	18882,25	0,12%		0,0001%				
13	12	01/18/11	19092,05	1,10%		0,0122%				
14	13	01/19/11	18978,32	-0,60%		0,0036%				
15	14	01/20/11	19046,54	0,36%		0,0013%				
16	15	01/21/11	19007,53	-0,21%		0,0004%				
17	16	01/24/11	19151,28	0,75%		0,0057%				
18	17	01/25/11	18969,45	-0,95%		0,0091%				
19	18	01/27/11	18684,43	-1,51%		0,0229%				
20	19	01/28/11	18395,97	-1,56%		0,0242%				
21	20	01/31/11	18327,76	-0,37%		0,0014%				
22	21	02/01/11	18022,22	-1,68%		0,0283%				
23	22	02/02/11	18090,62	0,38%		0,0014%				
24	23	02/03/11	18449,31	1,96%		0,0385%				
25	24	02/04/11	18008,15	-2,42%		0,0586%				
26	25	02/07/11	18037,19	0,16%		0,0003%				
27	26	02/08/11	17775,7	-1,46%		0,0213%				

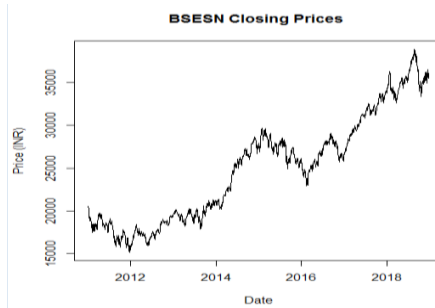
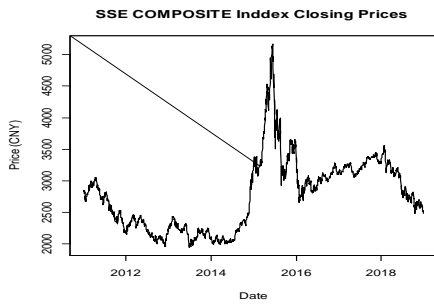
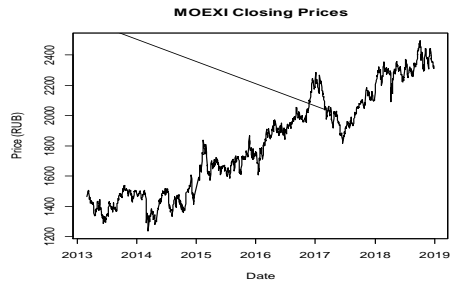
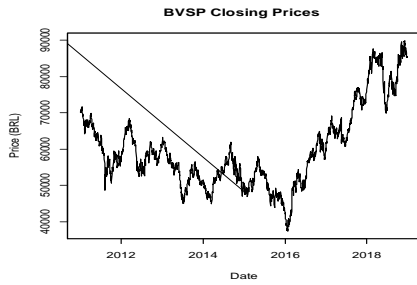
- China

	B	C	D	E	F	G	H	I	J
1	code	ISE(1C)	returns	Résiduals	returns square	variance	standard deviation	95%	99%
2	01/03/11	28830,73				0,010%	1,021%	-1,680%	-2,376%
3	01/04/11	28933,58	0,36%		0,0013%				
4	01/05/11	28502,97	-1,50%		0,0225%				
5	01/06/11	28608,82	0,37%		0,0014%				
6	01/07/11	28415,54	-0,68%		0,0046%				
7	01/10/11	28220,69	-0,69%		0,0047%				
8	01/11/11	28700,04	1,68%		0,0284%				
9	01/12/11	29038,72	1,17%		0,0138%				
10	01/13/11	29199,02	0,55%		0,0030%				
11	01/14/11	29226,96	0,10%		0,0001%				
12	01/17/11	28893,16	-1,15%		0,0132%				
13	01/18/11	29192,55	1,03%		0,0106%				
14	01/19/11	29013,19	-0,62%		0,0038%				
15	01/20/11	28514,94	-1,73%		0,0300%				
16	01/21/11	28808,74	1,03%		0,0105%				
17	01/24/11	28545,01	-0,92%		0,0085%				
18	01/25/11	28334,12	-0,74%		0,0055%				
19	01/26/11	28647,4	1,10%		0,0121%				
20	01/27/11	28812,39	0,57%		0,0033%				
21	01/28/11	28232,1	-2,03%		0,0414%				
22	01/31/11	28145,34	-0,31%		0,0009%				
23	02/01/11	28625,33	1,69%		0,0286%				
24	02/02/11	29274,22	2,24%		0,0502%				
25	02/03/11	29609,47	1,14%		0,0130%				
26	02/04/11	29718,96	0,37%		0,0014%				
27	02/07/11	29621,7	-0,33%		0,0011%				

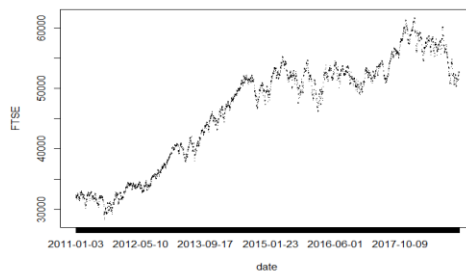
- South Africa

	A	B	C	D	E	F	G	H	I	J
1	N°	date	SHANG-SHG(1C)	Returns	Résiduals	returns square	variance	standard deviation	95%	99%
2	1	01/04/11	2852,648							
3	2	01/05/11	2838,593	-0,49%		0,00244%	0,019%	1,379%	-2,268%	-3,208%
4	3	01/06/11	2824,197	-0,51%		0,00259%				
5	4	01/07/11	2838,801	0,52%		0,00266%				
6	5	01/10/11	2791,809	-1,67%		0,02786%				
7	6	01/11/11	2804,047	0,44%		0,00191%				
8	7	01/12/11	2821,305	0,61%		0,00376%				
9	8	01/13/11	2827,713	0,23%		0,00051%				
10	9	01/14/11	2791,344	-1,29%		0,01676%				
11	10	01/17/11	2706,66	-3,08%		0,09491%				
12	11	01/18/11	2708,979	0,09%		0,00007%				
13	12	01/19/11	2758,097	1,80%		0,03229%				
14	13	01/20/11	2677,652	-2,96%		0,08762%				
15	14	01/21/11	2715,294	1,40%		0,01949%				
16	15	01/24/11	2695,72	-0,72%		0,00523%				
17	16	01/25/11	2677,432	-0,68%		0,00463%				
18	17	01/26/11	2708,814	1,17%		0,01358%				
19	18	01/27/11	2749,15	1,48%		0,02185%				
20	19	01/28/11	2752,75	0,13%		0,00017%				
21	20	01/31/11	2790,694	1,37%		0,01874%				
22	21	02/01/11	2798,96	0,30%		0,00087%				
23	22	02/09/11	2774,065	-0,89%		0,00798%				
24	23	02/10/11	2818,163	1,58%		0,02487%				
25	24	02/11/11	2827,328	0,32%		0,00105%				
26	25	02/14/11	2899,134	2,51%		0,06290%				
27	26	02/15/11	2899,237	0,00%		0,00000%				

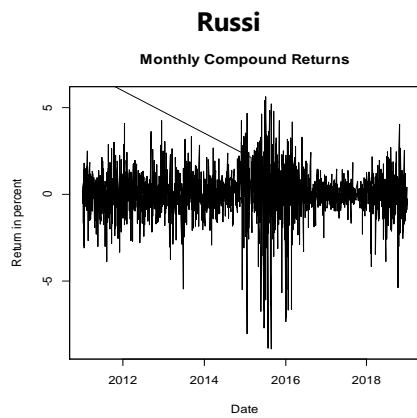
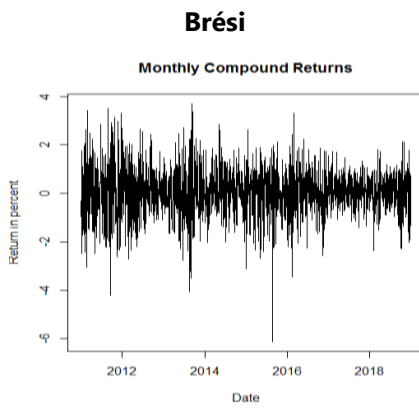
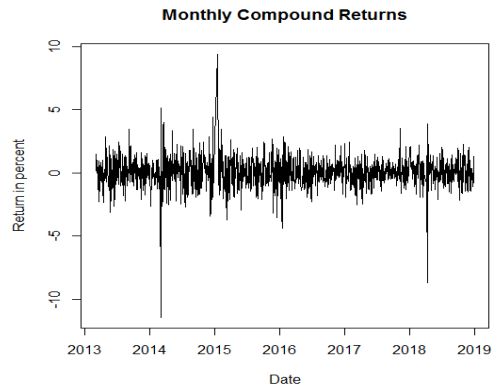
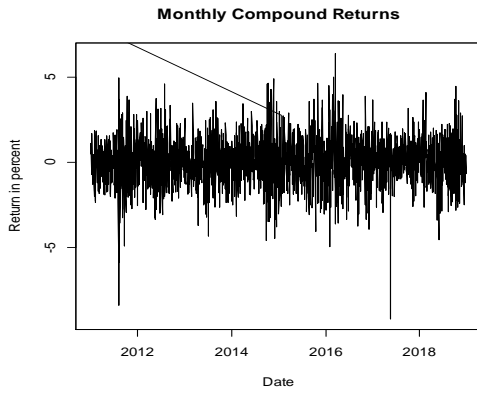
Annex 5: Volatility in the BRICS group's market indices



FTSE/JSE Closing Price

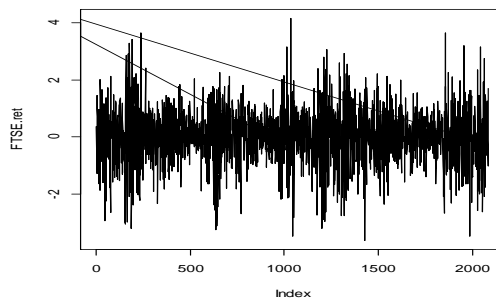


Annex 6: Daily returns of market indices



Inde

Chine



Afrique de sud

Annex 7: The best average model using ARIMA and the ARCH effect test

- Brazil

```
> fit1 <- auto.arima(BVSPI.ret, trace=TRUE, test="kpss", ic="bic")

Fitting models using approximations to speed things up...

ARIMA(2,0,2) with non-zero mean : Inf
ARIMA(0,0,0) with non-zero mean : 7098.224
ARIMA(1,0,0) with non-zero mean : 7018.447
ARIMA(0,0,1) with non-zero mean : 4536.125
ARIMA(0,0,0) with zero mean      : 7090.759
ARIMA(1,0,1) with non-zero mean : Inf
ARIMA(0,0,2) with non-zero mean : Inf
ARIMA(1,0,2) with non-zero mean : Inf
ARIMA(0,0,1) with zero mean     : 4529.139
ARIMA(1,0,1) with zero mean     : Inf
ARIMA(0,0,2) with zero mean     : Inf
ARIMA(1,0,0) with zero mean     : 7011.515
ARIMA(1,0,2) with zero mean     : Inf

Now re-fitting the best model(s) without approximations...

ARIMA(0,0,1) with zero mean      : 7096.414

Best model: ARIMA(0,0,1) with zero mean

> Box.test(fit1$residuals^2, lag=12, type="Ljung-Box")

Box-Ljung test

data: fit1$residuals^2
X-squared = 200.09, df = 12, p-value < 2.2e-16
```

- Russia

```
> fit1 <- auto.arima(MOEXI.ret, trace=TRUE, test="kpss", ic="bic")

Fitting models using approximations to speed things up...

ARIMA(2,0,2) with non-zero mean : Inf
ARIMA(0,0,0) with non-zero mean : 4479.893
ARIMA(1,0,0) with non-zero mean : 4194.135
ARIMA(0,0,1) with non-zero mean : Inf
ARIMA(0,0,0) with zero mean      : 4473.822
ARIMA(2,0,0) with non-zero mean : 4202.272
ARIMA(1,0,1) with non-zero mean : -24906.68
ARIMA(2,0,1) with non-zero mean : Inf
ARIMA(1,0,2) with non-zero mean : Inf
ARIMA(0,0,2) with non-zero mean : Inf
ARIMA(1,0,1) with zero mean     : Inf

Now re-fitting the best model(s) without approximations...

ARIMA(1,0,1) with non-zero mean : 4493.034

Best model: ARIMA(1,0,1) with non-zero mean

> Box.test(fit1$residuals^2,lag=12, type="Ljung-Box")

Box-Ljung test

data: fit1$residuals^2
X-squared = 47.401, df = 12, p-value = 3.972e-06
```

- India

```
> fit1 <- auto.arima(BSESNI.ret, trace=TRUE, test="kpss", ic="bic")

Fitting models using approximations to speed things up...

ARIMA(2,0,2) with non-zero mean : Inf
ARIMA(0,0,0) with non-zero mean : 5420.973
ARIMA(1,0,0) with non-zero mean : 5318.993
ARIMA(0,0,1) with non-zero mean : Inf
ARIMA(0,0,0) with zero mean     : 5415.138
ARIMA(2,0,0) with non-zero mean : 5318.674
ARIMA(3,0,0) with non-zero mean : 5525.787
ARIMA(2,0,1) with non-zero mean : Inf
ARIMA(1,0,1) with non-zero mean : Inf
ARIMA(3,0,1) with non-zero mean : Inf
ARIMA(2,0,0) with zero mean     : 5313.332
ARIMA(1,0,0) with zero mean     : 5312.267
ARIMA(1,0,1) with zero mean     : Inf
ARIMA(0,0,1) with zero mean     : 6527.545
ARIMA(2,0,1) with zero mean     : Inf

Now re-fitting the best model(s) without approximations...

ARIMA(1,0,0) with zero mean      : 5421.754

Best model: ARIMA(1,0,0) with zero mean

> Box.test(fit1$residuals^2,lag=12, type="Ljung-Box")

Box-Ljung test

data: fit1$residuals^2
X-squared = 269.6, df = 12, p-value < 2.2e-16
```

- China

```
> fit1 <- auto.arima(SSE.ret, trace=TRUE, test="kpss", ic="bic")

Fitting models using approximations to speed things up...

ARIMA(2,0,2) with non-zero mean : Inf
ARIMA(0,0,0) with non-zero mean : 6779.22
ARIMA(1,0,0) with non-zero mean : 6551.526
ARIMA(0,0,1) with non-zero mean : Inf
ARIMA(0,0,0) with zero mean      : 6771.696
ARIMA(2,0,0) with non-zero mean : 6551.044
ARIMA(3,0,0) with non-zero mean : 6728.932
ARIMA(2,0,1) with non-zero mean : Inf
ARIMA(1,0,1) with non-zero mean : Inf
ARIMA(3,0,1) with non-zero mean : Inf
ARIMA(2,0,0) with zero mean      : 6545.474
ARIMA(1,0,0) with zero mean      : 6544.147
ARIMA(1,0,1) with zero mean      : Inf
ARIMA(0,0,1) with zero mean      : 2876.236
ARIMA(0,0,2) with zero mean      : Inf
ARIMA(1,0,2) with zero mean      : Inf

Now re-fitting the best model(s) without approximations...

ARIMA(0,0,1) with zero mean      : 6779.133

Best model: ARIMA(0,0,1) with zero mean

> Box.test(fit1$residuals^2,lag=12, type="Ljung-Box")

      Box-Ljung test

data:  fit1$residuals^2
X-squared = 1104.7, df = 12, p-value < 2.2e-16
```

- South Africa

```
> fit1 <- auto.arima(FTSE.ret, trace=TRUE, test="kpss", ic="bic")

Fitting models using approximations to speed things up...

ARIMA(2,0,2) with non-zero mean : 5654.969
ARIMA(0,0,0) with non-zero mean : 5639.202
ARIMA(1,0,0) with non-zero mean : 5647.508
ARIMA(0,0,1) with non-zero mean : 5646.625
ARIMA(0,0,0) with zero mean      : 5632.884
ARIMA(1,0,1) with non-zero mean : 5642.761

Now re-fitting the best model(s) without approximations...

ARIMA(0,0,0) with zero mean      : 5632.884

Best model: ARIMA(0,0,0) with zero mean
```

```
> Box.test(fit1$residuals^2, lag=12, type="Ljung-Box")  
  
Box-Ljung test  
  
data: fit1$residuals^2  
X-squared = 299.21, df = 12, p-value < 2.2e-16
```

Annex 8: Estimation of VaR by the GARCH model

- Brazil at 1%

```
> report(res_garch01_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99)  
VaR Backtest Report  
=====
```

Model:		sGARCH-norm
Backtest Length:	1854	
Data:		

```
=====
```

alpha:		1%
Expected Exceed:	18.5	
Actual VaR Exceed:	32	
Actual %:		1.7%

Unconditional Coverage (Kupiec)

Null-Hypothesis:	Correct Exceedances
LR.uc Statistic:	8.11
LR.uc Critical:	6.635
LR.uc p-value:	0.004
Reject Null:	YES

Conditional Coverage (Christoffersen)

Null-Hypothesis:	Correct Exceedances and Independence of Failures
LR.cc Statistic:	10.497
LR.cc Critical:	9.21
LR.cc p-value:	0.005
Reject Null:	YES

- Brazil at 5%

```
> report(res_garch01_roll, type = "VaR", VaR.alpha = 0.05, conf.level = 0.95)
VaR Backtest Report
=====
Model:                               sGARCH-norm
Backtest Length:                      1854
Data:

=====
alpha:                                5%
Expected Exceed:                      92.7
Actual VaR Exceed:                   115
Actual %:                             6.2%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                      Correct Exceedances
LR.uc Statistic:                      5.263
LR.uc Critical:                       3.841
LR.uc p-value:                        0.022
Reject Null:                          YES

Conditional Coverage (Christoffersen)
Null-Hypothesis:                      Correct Exceedances and
                                         Independence of Failures
LR.cc Statistic:                      5.779
LR.cc Critical:                       5.991
LR.cc p-value:                        0.056
Reject Null:                          NO
```

- Russia at 1 %

```
> report(res_garch11_rol1, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99)
VaR Backtest Report
=====
Model:                                sGARCH-norm
Backtest Length:                       1310
Data:

=====
alpha:                                  1%
Expected Exceed:                        13.1
Actual VaR Exceed:                      20
Actual %:                                1.5%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                        Correct Exceedances
LR.uc Statistic:                        3.162
LR.uc Critical:                          6.635
LR.uc p-value:                          0.075
Reject Null:                             NO

Conditional Coverage (Christoffersen)
Null-Hypothesis:                        Correct Exceedances and
                                           Independence of Failures
LR.cc Statistic:                        4.194
LR.cc Critical:                          9.21
LR.cc p-value:                          0.123
Reject Null:                             NO
```

- Russia at 5

```
> report(res_garch11_rol1, type = "VaR", VaR.alpha = 0.05, conf.level = 0.95)
VaR Backtest Report
=====
Model:                                sGARCH-norm
Backtest Length:                       1310
Data:

=====
alpha:                                  5%
Expected Exceed:                        65.5
Actual VaR Exceed:                      84
Actual %:                                6.4%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                        Correct Exceedances
LR.uc Statistic:                        5.069
LR.uc Critical:                          3.841
LR.uc p-value:                          0.024
Reject Null:                             YES

Conditional Coverage (Christoffersen)
Null-Hypothesis:                        Correct Exceedances and
                                           Independence of Failures
LR.cc Statistic:                        6.348
LR.cc Critical:                          5.991
LR.cc p-value:                          0.042
Reject Null:                             YES
```

- India at 1 %

```
> report(res_garch10_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99)
VaR Backtest Report
=====
Model:                               sGARCH-norm
Backtest Length:                      1840
Data:

=====
alpha:                                 1%
Expected Exceed:                       18.4
Actual VaR Exceed:                     72
Actual %:                               3.9%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                       Correct Exceedances
LR.uc Statistic:                       90.854
LR.uc Critical:                        6.635
LR.uc p-value:                         0
Reject Null:                           YES

Conditional Coverage (Christoffersen)
Null-Hypothesis:                       Correct Exceedances and
                                         Independence of Failures
LR.cc Statistic:                       92.365
LR.cc Critical:                        9.21
LR.cc p-value:                         0
Reject Null:                           YES
> |
```

- India at 5 %

```
> report(res_garch10_roll, type = "VaR", VaR.alpha = 0.05, conf.level = 0.95)
VaR Backtest Report
=====
Model:                               sGARCH-norm
Backtest Length:                      1840
Data:

=====
alpha:                                 5%
Expected Exceed:                       92
Actual VaR Exceed:                     149
Actual %:                               8.1%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                       Correct Exceedances
LR.uc Statistic:                       31.562
LR.uc Critical:                        3.841
LR.uc p-value:                         0
Reject Null:                           YES

Conditional Coverage (Christoffersen)
Null-Hypothesis:                       Correct Exceedances and
                                         Independence of Failures
LR.cc Statistic:                       31.563
LR.cc Critical:                        5.991
LR.cc p-value:                         0
Reject Null:                           YES
> |
```

- China at 1%

```
> report(res_garch01_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99)
VaR Backtest Report
=====
Model:                               sGARCH-norm
Backtest Length:                      1824
Data:

=====
alpha:                                1%
Expected Exceed:                      18.2
Actual VaR Exceed:                   49
Actual %:                             2.7%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                      Correct Exceedances
LR.uc Statistic:                      35.851
LR.uc Critical:                       6.635
LR.uc p-value:                        0
Reject Null:                          YES

Conditional Coverage (Christoffersen)
Null-Hypothesis:                      Correct Exceedances and
                                         Independence of Failures
LR.cc Statistic:                      36.176
LR.cc Critical:                       9.21
LR.cc p-value:                        0
Reject Null:                          YES
> |
```

- China at 5%

```
> report(res_garch01_roll, type = "VaR", VaR.alpha = 0.05, conf.level = 0.95)
VaR Backtest Report
=====
Model:                               sGARCH-norm
Backtest Length:                      1824
Data:

=====
alpha:                                5%
Expected Exceed:                      91.2
Actual VaR Exceed:                   101
Actual %:                             5.5%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                      Correct Exceedances
LR.uc Statistic:                      1.073
LR.uc Critical:                       3.841
LR.uc p-value:                        0.3
Reject Null:                          NO

Conditional Coverage (Christoffersen)
Null-Hypothesis:                      Correct Exceedances and
                                         Independence of Failures
LR.cc Statistic:                      4.301
LR.cc Critical:                       5.991
LR.cc p-value:                        0.116
Reject Null:                          NO
```

- South Africa at 1%

```
> report(res_garch11_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99)
VaR Backtest Report
=====
Model:                               sGARCH-norm
Backtest Length:                      1965
Data:

=====
alpha:                                1%
Expected Exceed:                       19.7
Actual VaR Exceed:                     50
Actual %:                              2.5%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                       Correct Exceedances
LR.uc Statistic:                       33.171
LR.uc Critical:                         6.635
LR.uc p-value:                          0
Reject Null:                            YES

Conditional Coverage (Christoffersen)
Null-Hypothesis:                       Correct Exceedances and
                                         Independence of Failures
LR.cc Statistic:                       33.237
LR.cc Critical:                         9.21
LR.cc p-value:                          0
Reject Null:                            YES
```

- South Africa at 5%

```
> report(res_garch11_roll, type = "VaR", VaR.alpha = 0.05, conf.level = 0.95)
VaR Backtest Report
=====
Model:                               sGARCH-norm
Backtest Length:                      1965
Data:

=====
alpha:                                5%
Expected Exceed:                       98.2
Actual VaR Exceed:                     140
Actual %:                              7.1%

Unconditional Coverage (Kupiec)
Null-Hypothesis:                       Correct Exceedances
LR.uc Statistic:                       16.596
LR.uc Critical:                         3.841
LR.uc p-value:                          0
Reject Null:                            YES

Conditional Coverage (Christoffersen)
Null-Hypothesis:                       Correct Exceedances and
                                         Independence of Failures
LR.cc Statistic:                       21.468
LR.cc Critical:                         5.991
LR.cc p-value:                          0
Reject Null:                            YES
```

Annex 9: Chi-2 distribution

	p value												
f	0.995	0.99	0.975	0.95	0.9	0.75	0.5	0.25	0.1	0.05	0.025	0.01	0.005
1	0.00	0.00	0.00	0.00	0.02	0.10	0.45	1.32	2.71	3.84	5.02	6.63	7.88
2	0.01	0.02	0.05	0.10	0.21	0.58	1.39	2.77	4.61	5.99	7.38	9.21	10.60
3	0.07	0.11	0.22	0.35	0.58	1.21	2.37	4.11	6.25	7.81	9.35	11.34	12.84
4	0.21	0.30	0.48	0.71	1.06	1.92	3.36	5.39	7.78	9.49	11.14	13.28	14.86
5	0.41	0.55	0.83	1.15	1.61	2.67	4.35	6.63	9.24	11.07	12.83	15.09	16.75
6	0.68	0.87	1.24	1.64	2.20	3.45	5.35	7.84	10.64	12.59	14.45	16.81	18.55
7	0.99	1.24	1.69	2.17	2.83	4.25	6.35	9.04	12.02	14.07	16.01	18.48	20.28
8	1.34	1.65	2.18	2.73	3.49	5.07	7.34	10.22	13.36	15.51	17.53	20.09	21.95
9	1.73	2.09	2.70	3.33	4.17	5.90	8.34	11.39	14.68	16.92	19.02	21.67	23.59
10	2.16	2.56	3.25	3.94	4.87	6.74	9.34	12.55	15.99	18.31	20.48	23.21	25.19
11	2.60	3.05	3.82	4.57	5.58	7.58	10.34	13.70	17.28	19.68	21.92	24.72	26.76
12	3.07	3.57	4.40	5.23	6.30	8.44	11.34	14.85	18.55	21.03	23.34	26.22	28.30
13	3.57	4.11	5.01	5.89	7.04	9.30	12.34	15.98	19.81	22.36	24.74	27.69	29.82
14	4.07	4.66	5.63	6.57	7.79	10.17	13.34	17.12	21.06	23.68	26.12	29.14	31.32
15	4.60	5.23	6.26	7.26	8.55	11.04	14.34	18.25	22.31	25.00	27.49	30.58	32.80

Source: Passel, 2016

Statistical Analysis of Road Traffic Accidents (RTAs) in Sri Lanka

D.S. Kodithuwakku¹, T.S.G. Peiris²

Abstract

Road Traffic Accidents (RTAs) are one of the most prominent public health problems as it is a leading cause of death by injury and all deaths globally. This study, therefore, intended to determine the significant factors associated with RTAs in Sri Lanka (2005 - 2019) and the impact of those factors using data obtained from the Department of Police, Sri Lanka. The leading causes for RTAs are overtaking, speed driving and diversion and about 80% RTAs are due to these factors. The percentage of RTAs due to alcohol consumption by the driver is around 9%. Both exploratory and confirmatory factors analysis found that the causes for RTAs can be classified into two independent factors namely, (i) negligence of pedestrians & drivers and (ii) lack of attention of the driver. These factors are invariant by the factor extraction method and the type of orthogonal rotation. The condition of road the surface, light condition of the road, the situation of weather, type of vehicle and age of the driver are significantly influential factors in fatal accidents. The highest percentage of fatal accidents have occurred when the road is wet and light condition is poor during night. The inferences derived from this study can be effectively used for policy decisions related to traffic in order to minimize RTAs in Sri Lanka. The study confirmed the benefits of data-driven decision-making for policy decision process.

Keywords: Data Driven Decision Making, Road Traffic Accidents, Severity of Accident

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1. Introduction

Road safety has been recognized by the 2030 Agenda for Sustainable Development as a precondition to ensure strengthened well-being and healthy lives and to create inclusive, sustainable and resilient cities (WHO, 2018). The WHO (2018) stated that the disabilities and injuries that occur due to Road Traffic Accidents (RTAs) and the safety of roads influence other issues related to community well-being as these factors contribute to the hindrance of human activity. Diseases like diabetes, chronic obstructive pulmonary diseases, strokes and heart diseases become widespread due to self-imposed limitations to walking, cycling and taking public transport by citizens and, increased motorization has also been linked to illnesses in the respiratory system. Ensuring road traffic safety and supporting active travel also contribute to reducing the number of preventable deaths (WHO, 2018). Thus, RTAs are a prominent health-care problem that has a major influence on the universal health situation. However, less attention has been given to analyzing past data related to RTAs. Despite traffic law implementations, technological advances, and improvements in the traffic education systems, the number of traffic fatalities has not decreased substantially over the year. This indicates that although efforts are being made in the right direction, there is a lack of overall understanding of all the contributing factors due to not investigating the data deeply.

Nevertheless, various authors have presented multiple explanations for the reduction in crashes seen in recent years (Nasiri et al., 2019; Demissie, 2017; Dhananjaya & Alibuhtto, 2016). Some factors that influence the reduction are the use of safety belts, safer vehicles, and better roads, strengthened funding for safety infrastructure improvements.

Sri Lankan Police have identified 25 causes for RTAs. However, the direct impact of each attribute has not been investigated via comprehensive statistical analysis. Thus, it is vital to identify the key factors out of the causes listed as recklessness of the driver, negligent of the driver, indiscipline driving, lack of knowledge (road rules and regulations, road conditions, weather conditions, conditions of the vehicle, knowledge regarding apparatus, controls, equipment), human error, fatigue or stress, road infrastructure defects, not planning the trip, duty poor health condition, lack of driving experience and skills, driving under the influence of alcohol, failure to check power, speeding,

not wearing the safety belt, pedestrians not following road rules, not following the indications of traffic lights, not knowing the meanings of the different road signs markings signals, lack of skills driving during rains, winds, fog and mist, failure to obey road rules and regulations, driving after taking medication, trying to beat uptime, failure in respecting the rights of others, failure in recognizing civic responsibility, unsatisfactory enforcement by some police officer and not keeping the proper distance.

2. Materials and Methods

2.1 Secondary Data

This study consists with panel data of RTAs in Sri Lanka which were gathered from the Sri Lanka Police. All the data are extent the period of 2005 - 2019. Sri Lanka Police have announced main seven causes of RTAs by combining the causes mentioned in table 1. They are speed driving, overtaking, diversion, mechanical faults of vehicle, alcohol consumption of driver, negligence of pedestrians and other reasons.

2.2 Statistical Analysis

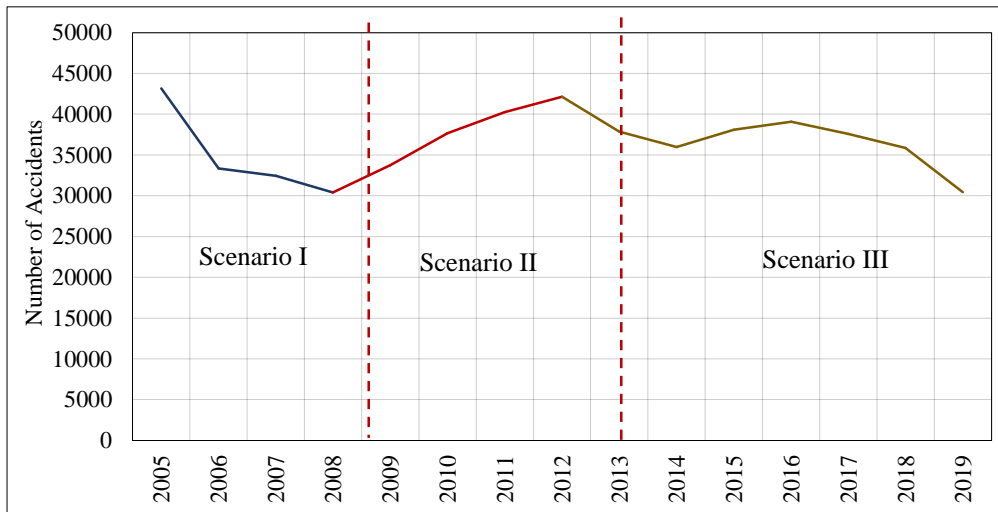
The basic exploratory data analyses and both Exploratory Factor Analysis (EFA) and the Confirmatory Factor Analysis (CFA) are used.

3. Results and Discussion

3.1 Identification of Three Scenarios

In terms of road accidents in Sri Lanka over the last 15 years, there can be seen considerable changes in different periods. Thus, the entire time period from 2005 to 2019 was considered as three main scenarios based on the trend in the annual number of accidents, as shown in figure 1. Scenario I, II and III can thus be considered as the periods: 2005 - 2008, 2009 - 2012 and 2013 – 2019, respectively.

Figure 1: RTAs in Sri Lanka (2005 - 2019)



Source: Survey Data, 2022

It was found that during the period from 2005 to 2019, the number of total accidents has varied from a minimum of 30,420 (2008) to a maximum of 43,171 (2005), with a mean of 36,539 and SE of mean of 1,006.

3.2 Comparison of RTAs in Three Scenarios

The useful descriptive statistics for the three scenarios are shown in table 2.

Table 1: Basic Statistics of each Scenarios by Types of Accidents

Type of Accident	Scenario I		Scenario II		Scenario III	
	Mean	SE of Mean	Mean	SE of Mean	Mean	SE of Mean
Fatal	2,135 (6.1%)	24.3	2,405 (6.3%)	81.2	2,640 (7.2%)	121
Grievous	4,919 (14.1%)	71.7	6,424 (16.7%)	413	7,922 (21.8%)	281
Minor	12,430 (35.7%)	661	12,908 (33.6%)	724	12,918 (35.5%)	472
Damage	15,363 (44.1%)	2,186	16,708 (43.5%)	687	12,937 (35.5%)	706
Total	34,847		38,445		36,417	

Note: () represents the percentage contribution with respect to the total

According to table 1, of the three scenarios, the highest number of fatal, grievous and minor accidents have occurred during scenario III. Moreover, the SE of the mean of both grievous and minor accidents are higher in scenario II, and SE of mean of fatal accidents are higher in scenario III. Furthermore, the highest number of damage accidents are in scenario II, but the SE of the mean is lowest in scenario II. The percentage increases in fatal and grievous accidents in scenario III compared to scenario II are 10% and 23%, respectively. In contrast, damage types of accidents have reduced by 23% during scenario III compared to scenario II. Minor types of accidents are almost the same in both scenarios.

3.3 Main Reasons for RTAs

Though Sri Lanka Police has identified 25 causes for RTAs, the reasons for RTAs have been classified into seven, as shown in table 2. Furthermore, the category of ‘others’ has not been well defined. Table 2 describes the mean values of each observed variable and the SE of the mean to recognize the scattering of RTAs data over 15 years (2005 - 2019).

Table 2: Basic Statistics of RTAs (per year) among the Seven Categories during 2005 – 2019

Reasons	Mean	SE of Mean	% of contribution with respect to the total of first six (excluding others)
Overtaking	5,861	16.5	31.6
Speed driving	4,606	13.0	24.8
Diversion	5,024	14.1	27.1
Alcohol consumption of driver	1,610	4.5	8.7
Mechanical faults of vehicle	453	1.3	2.4
Negligence of pedestrians	1,006	2.8	5.4
Others	16,971	47.8	-
Total	35,531		

Source: Survey Data, 2022

Of the 25 causes identified by Sri Lanka Police, the other category in table 2 represents the various minor causes of RTAs which do not belong to the six major reasons described in the first column in table 2. Furthermore, though the

number in the other category is very high (47.8% of the total), it is considered as least impact on the society compared to the impact of the other six causes.

Column 4 in Table 2 represents the percentage contribution concerning the total of major causes for RTAs. It can be seen that, nearly more than 80% RTAs were due to overtaking, diversion, and speed driving. Furthermore, it should be noted that RTAs due to alcohol consumption of the driver is significantly less (8.7%).

3.4 Use of Exploratory Factor Analysis (EFA)

As it was found that there is a significant association among six variables shown in table 2, it is necessary to find any common factors linked to those six variables and consequently, EFA was carried out. The significance of Bartlett’s Test of Sphericity (Table 3) ratified that the observed correlation matrix is significantly different from the identity matrix, and thus, common factors due to inter-correlation can be investigated. Results in table 3 also indicated that the KMO statistic (0.780) is greater than 0.6, confirming that data satisfying sample adequacy for EFA.

Table 3: Results of KMO and Bartlett’s test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.780
Bartlett's Test of Sphericity	Approx. Chi-Square	92.496
	Df	15
	Sig.	0.00

Source: Survey Data, 2022

The results of the JB normality test for each variable concluded that all the variables are not significantly deviate from normal distribution at the 5% level. Thus, the common factors can be extracted using Maximum Likelihood Factoring (MLF) in addition to Principal Axis Factoring (PAF) and Principle Component Analysis (PCF). Furthermore, as the variances of the six variables are unevenly distributed, EFA was carried out for the standardized data, and thus, eigenvalue analysis was carried out for the correlation matrix.

3.5 Eigen Analysis for Correlation Matrix Analysis

Eigen analysis for the correlation matrix in table 4 indicated that only one eigenvalue is greater than one. However, the second eigenvalue is also close to 1. Thus, according to Kaiser’s rule (Kaiser, 1960), two factors can be used

to explain the observed correlation matrix of six variables. These two factors accounted for 91% of the total observed variance of the six variables confirming that the initial 6 dimensions system can be reduced to a 2 dimensions system.

Table 4: Eigenvalue Analysis based on the Correlation Matrix of the 7 Variables

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.480	74.669	74.669	4.480	74.669	74.669
2	.995	16.585	91.254	.995	16.585	91.254
3	.350	5.837	97.090			
4	.084	1.398	98.488			
5	.057	.943	99.432			
6	.034	.568	100.000			

Source: Survey Data, 2022

3.6 Extraction and Rotation of Factors

Factors were initially extracted using the PCF method followed by PAF and MLF. It was found that the results are invariant on the type of extraction method. The identified factors need to be rotated to get influential factors (Peiris, 2018). It was found that factors were invariant of the type of orthogonal rotation (Table 5).

Table 5: Summary of the 2 - Factor Model

Extraction Methods	Type of rotation	Factor 1	Factor 2
PCF	Varimax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver
	Quartimax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver

	Equamax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver
PAF	Varimax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver
	Quartimax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver
	Equamax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver
MLF	Varimax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver
	Quartimax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver
	Equamax	Speed driving Mechanical faults of vehicle Negligence of pedestrians	Overtaking Diversion Alcohol consumption of driver

Source: Survey Data, 2022

3.7 Factor Score Coefficient

Of the three types of extraction methods and three types of rotation methods, PCF with the Varimax rotation method is more popular and efficient (Peiris, 2018). Therefore, the factor score coefficient was obtained for the combination of PCF and the Varimax rotation method (Table 6).

Table 6: Factor Score Coefficient of Selected Factors from Varimax (PCF)

Reasons	Component	
	1	2
Overtaking	.065	.232
Speed driving	.187	.113
Diversion	-.041	.363
Alcohol consumption of driver	-.329	.602
Mechanical faults of vehicle	.448	-.232
Negligence of pedestrians	.457	-.233

Source: Survey Data, 2022

As the EFA was carried out for the correlation matrix, initial variables were standardized prior EFA. Thus, the two factors (F1 and F2) can be defined as,

$$F1 = 0.187 * [(Speed\ driving - 4606.47) / 1875.40] + 0.448 * [(Mechanical\ fault\ of\ vehicle - 452.67) / 254.07] + 0.457 * [(Negligence\ of\ pedestrians - 1006.00) / 438.17]$$

$$F2 = 0.232 * [(Overtaking - 5860.73) / 1859.86] + 0.363 * [(Diversion - 5024.27) / 790.29] + 0.602 * [(Alcohol\ consumption\ of\ driver - 1609.53) / 326.84]$$

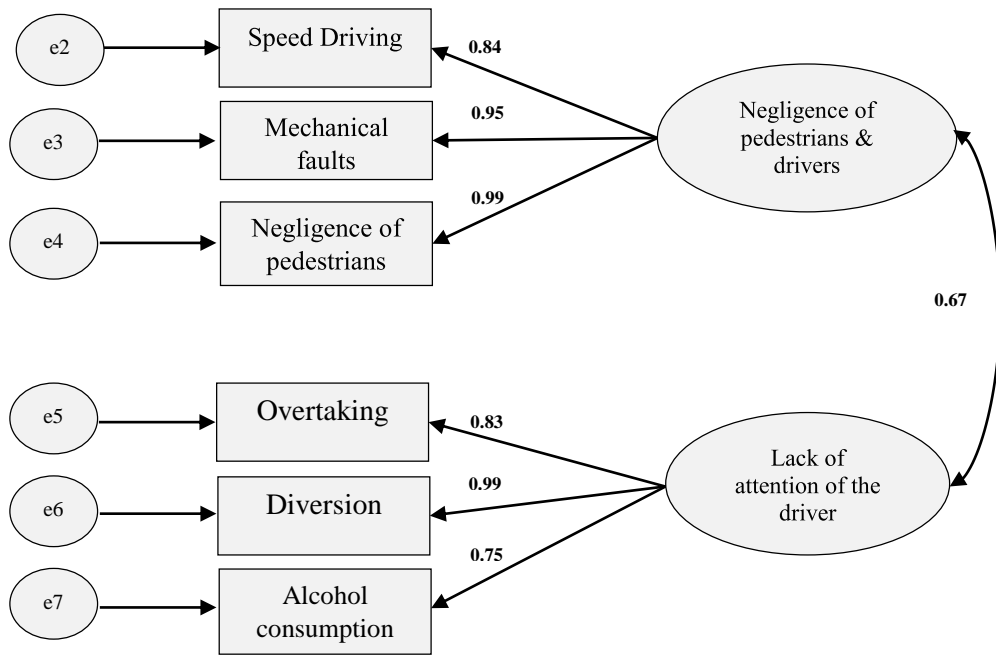
The two factors were named as, “negligence of pedestrians & drivers” and “lack of attention of the driver”.

3.8 Confirmatory Factor Analysis (CFA)

In order to further justify the structure of the two factors identified using EFA, CFA was also carried out and results are shown in figure 3.

According to figure 3, all the variables of the two factors indicated high loading values (> 0.8). This justified the validity of the variables selected for the two factors using EFA. The statistics of the model justification is shown in table 8.

Figure 3: Standardized Parameter Estimates for 2 - Factor CFA



Source: Survey Data, 2022

3.8.1 Evaluating Model Fit

Table 7: Model Chi-Square Statistics (Finalized Model)

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	13	23.369	8	.003	2.921
Saturated model	21	.000	0		
Independence model	6	115.965	15	.000	7.731

Source: Survey Data, 2022

The results in table 7 indicate that the chi square statistic ($\chi^2_8 = 253.369$, $p = 0.003$) is significant, confirming that the hypothesized model significantly fits the data. As this test is sensitive to sample size, various goodness-of-fit indices, have been suggested for the evolution the model fit. Some of the statistical indices generated from SPSS are shown in table 8.

Table 8: Model Fit Summary of Finalized Model

RMSEA	.070
NFI	.798
NNFI (TLI)	.815
CFI	.848
GFI	.742
AGFI	.822
PGFI	.283
PNFI	.426

Source: Survey Data, 2022

RMSEA is close to 0. All other indices in table 8 are higher than the critical value of the corresponding indices confirming that the hypothesized model fits the data adequately.

3.9 Association between Severity of Accident and Other Common Factors

In the database, the severity of the accident has been classified as fatal and non-as fatal, and therefore, the analysis of a 2-way frequency table was carried out to find the association between the severity of the accident and condition of the road, light condition of the road, status of weather, type of vehicle and age of the driver. The results of the Chi-square analysis and the percentage of fatal accidents for each level with the main variable are shown in table 9.

Table 9: Association between Main Variables and Severity of Accident

Main Variable	Category	% Fatal accident	Test statistic and p value
<i>Road Characteristics</i>			
Road surface	Dry	5.6	$\chi_1^2 = 250.507$ p = .000
	Wet	7.7	
Light condition	Day light	4.7	$\chi_2^2 = 2582.049$ p = .000
	Night, improper street lighting	8.4	
	Night, good street lighting	5.8	
<i>Time & Environmental Characteristics</i>			
Weather	Clear	5.6	$\chi_1^2 = 322.418$ p = .000
	Humid	7.7	
<i>Vehicle Characteristics</i>			
Vehicle type	Two wheels	6.1	$\chi_2^2 = 62.542$ p = .000
	Three wheels	5.6	

	More than three wheels	5.6	
Human & Accident Characteristics			
Age of driver	Less than 18 years	6.5	$\chi^2_3 = 52.202$ p = .000
	18 - 40 years	5.7	
	40 - 60 years	5.6	
	More than 60 years	5.8	

Source: Survey Data, 2022

As all the Chi-square test statistics are significant in table 9 and as the corresponding p values are less than 5%, it can be concluded with 95% confidence that the condition of the road surface, light condition of the road, the situation of the weather, the type of the vehicle and the age of the driver are significantly influential factors on fatal accidents.

The percentage of fatal accidents when the road surface is wet (7.7%) is significantly higher than that when the road is dry (5.6%). The percentage of fatal accidents during the night with improper street lighting (8.4%) is significantly higher than that of during the night with good street lighting (5.8%) as well as that of during the daylight (4.7%). These results were obtained by comparing two binomial distributions separately. The rate of fatal accidents when humid weather (7.7%) is significantly higher than that in clear weather (5.6%). The percentage of fatal accidents by two wheels vehicles (6.1%) is significantly higher than three wheels (5.6%) and four wheels vehicles (5.6%). When comparing three binomial distributions separately, the percentage of fatal accidents when the driver's age is between 18 - 40 years (5.7%) is significantly higher than when the driver's age is between 40 - 60 years. Moreover, the percentage of fatal accidents when the driver's age is above 60 years (5.8%) is significantly higher than when driver's age falls between 40 - 60 years. Similarly, the percentage of fatal accidents when the driver's age is less than 18 years (6.5%) is significantly higher than when the driver's age is more than 60 years.

4. Conclusions and Recommendations

4.1 Conclusions

The percentage of fatal accidents has increased from 6.1% (2005 - 2008) to 7.2% (2013 - 2019). In contrast, damages have dropped from 44.1% to 35.5% during the same time period. The percentage of grievous accidents has

increased from 14.1% (2005 - 2008) to 21.8% (2013 - 2019). However, minor accidents have dropped from 35.7% to 35.5% during the same period.

The two common factors were identified irrespective of factor extraction and rotation methods. (i) factor 1: negligence of pedestrians & drivers (ii) factor 2: lack driver's attention. Moreover, the other critical factors associated with fatal accidents are wet road surfaces, nights with improper street lighting, rural areas, humid weather, two wheels vehicles and the age of drivers who are less than 18 years.

4.2 Recommendations

Pedestrians should be educated on the using sidewalks, safe road crossing procedures, and watchfulness while crossing roads.

Traffic signalization, pedestrian bridges and pavement tunnels are good alternatives to prevent pedestrian accidents as they allow pedestrians to cross the road without coming into contact with vehicles.

Lane driving should be strictly followed, and drivers should be encouraged to use signals.

Implementation of proper road maintenance, properly designed road labels, erect road signs and warning signals that suit all climate changes, maintenance of proper road conditions, traffic conditions, and other special road condition requirements and the construction of bumping in appropriate locations along with the removal of all unauthorized bumping on the roads are other alternate steps which could be taken to prevent pedestrian accidents.

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Customer's Perspectives on Internet Banking based on E-S-Qual Model

Manjula Gunarathna¹

Abstract

In Sri Lanka, the credit growth the banking system improved in 2020 compared to 2019 regardless of the adverse economic effects caused by the ongoing pandemic and nationwide and district-wide lock-down periods. A significant increase was noticed in the usage of internet banking as people were considerably confined to their homes. Consequently, this study focuses on recognizing the view of customers on internet banking based on the E-S-Qual model. This model was established to measure the quality of e-service. Both exploratory and confirmatory factors analyses are classified into three independent factors namely, (i) System availability & fulfilment (ii) Efficiency and (iii) Privacy as common factors of internet banking. Respondents between the ages of 20 to 30 have shown positive perceptions on these three internet banking factors according to the cross-tabulation results. It was also revealed that the female respondents show a higher positive perception (76.9%) in comparison to males (23.1%) on the privacy of internet banking.

Keywords: *E-S-Qual Model, Customer Perception, Internet Banking*

1. Introduction

Information technology is taking over modern-day industries, including the banking sector. The internet provides a convenient channel for people to access services and for businesses to connect with their customers, especially since the use of personal computers to access the internet and the World Wide Web have risen significantly. The trend of providing services through the internet has significantly risen in recent times. This kind of banking is known as Internet Banking (Altun, 2012) (Semantics). Internet banking originated in the early 1990. This beginning of Internet Banking created a phenomenal

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system, Internet banking (Semantics). This system allows banking customers to access their accounts, carry out transactions or simply obtain banking information through the internet (Rajesh, 2007).

The main contributor to economic growth in Sri Lanka is the service sector. The financial institutions mainly dominate the service sector. The financial sector is accountable for 72.5% of the total assets within the financial system as per the end of 2020 data (Central Bank of Sri Lanka - CBSL, 2020). By the end of the year 2020, the banking system of Sri Lanka consisted of 24 Licensed Commercial Banks (LCBs) and 6 Licensed Specialized Banks (LSBs), adding up to 30 banks in total. The banking sector promotes financial inclusion by widening banking services and the banking network, supporting the financial intermediation of the economy. In 2020, due to the restrictions imposed on travelling to banks to obtain their services, banks introduced products and services accessible through technology-based mediums to facilitate financial inclusion (CBSL, 2020). In Sri Lanka, banking customers are moving steadily towards internet banking due to the on-going pandemic. According to the Central Bank of Sri Lanka (2020), significant growth was seen in internet usage as a result of travel restrictions and work-from-home engagements imposed due to the COVID-19.

Thus, with the rise of internet banking, there is a clear requirement to study how consumers evaluate e-services and develop e-loyalty. The main determinant of success or failure of e-commerce is the quality of service. As practitioners focus mainly on improving usability automated services have lagged behind (Santos, 2003). In order to reap the benefits of internet banking to promote economic growth of a country, Nupur (2010) highlighted the importance of better quality and increased internet access, designing and developing new features for internet banking, developing a solid legal and regulatory framework and promoting domestic internet usage. The popularization of internet banking has led to the creation of service quality (SERVQUAL) dimensions to measure customer satisfaction. SERVQUAL developed by Zeithaml (1988), is extensively utilized to measure customer satisfaction. According to Mols (2000), the wide use of SERVQUAL results from the belief that home banking will bring a drastic change in how banks maintain their relationship with customers. The E-S-QUAL model proposed by Parasuraman et al. (2005) is a more refined and extended version of SERVQUAL. According to this model, efficiency, fulfilment, system

availability and privacy are the four parameters to measure the quality of e-services.

Efficiency – The main advantages of online shopping are perceived to be saving time and convenience; thus, efficiency is a vital factor in e-commerce (Ranganathan & Ganapathy, 2002). Efficiency, in simple terms, is the speed and the ease with which the site can be accessed.

Fulfilment – The extent to which the offers on order delivery or the availability of items are fulfilled. Since maintaining promises made to customers and delivering accurate items are explicitly linked with customer satisfaction, fulfilment is a vital deciding factor of the quality in an online shop (Yang & Fang, 2004).

System availability – Related to the proper technical functioning of the online site. Customers are often disappointed by missing links or buttons that do not work. Then the retailer loses their opportunity to build customer loyalty (Wachter, 2002).

Privacy – The extent to which the site protects customer information. The risk of maltreating customer information stops people from purchasing goods and services online. However, online retailers are becoming more aware of the importance of establishing consumer privacy (Ranganathan and Ganapathy, 2002). Privacy is a strong determinant of customer intention to purchase goods and services online (Loiacono et al., 2002), of customer satiation (Szymanski and Hise, 2000) and the quality of the overall site (Yoo and Donthu, 2001).

Consequently, this study's objective is to determine customers' perspective on internet banking based on E-S-QUAL model.

2. Literature Review

The core capabilities of banks: products, channels and advice are promoted through the internet. Then the banks entered the market of e-commerce as providers of their products. Some banks did not establish internet banking initially as they failed to see the benefits it brought. According to Polatoglu and Kin (2001), the average transaction cost of internet banking is a mere one-twentieth of a teller transaction.

According to Rajesh (2007), the use of internet banking was stagnant during 1996 and 1998 as less than 10% of the market was using the service.

According to Ho and Wu (1999), five factors that determine customer satisfaction. These factors are: logistic support, technical characteristics, features of information, presentation of the home page and product personality (Ho and Wu, 1999). Due to the lack of confidence in technology-based services, the utilization of internet banking has been rejected by most customers (Ho and Wu, 1999).

Situating service quality and customer satisfaction within the internet banking domain introduces a whole perspective to finding answers to the research question of customer perspective on internet banking in Sri Lanka. Customer's perception of internet banking, together with preferred service quality, are major determinants of a bank's success (Gupta & Bansal, 2012). Customer satisfaction, in simple terms, is meeting the level of expectations of a customer for a given good or service (Afrin, 2012). Customer satisfaction is considered a key factor in the field of internet banking (Devi & Revathy, 2011). Establishing a high-service quality is a key contributor to generating high levels of customer satiation. As customer satisfaction is vital to establishing customer retention and profitability of the firm, the final goal of all firms is to improve the level of customer satisfaction (Sharma & Malviya, 2014). Many studies have been conducted to measure the impact of service quality on customer satisfaction in a typical banking environment; however, the studies that focus on the impact of service quality on customer satisfaction in the e-banking sector are limited in number (Saha & Zhao, 2005). According to Zeithaml, et al., (2000), more research needs to be conducted on the quality dimensions of e-services. Consequently, this study attempts to identify customers' perspectives on internet banking.

3. Methodology

Banking customers whose bank provides e-banking services and who have access to the internet and are proficient in utilizing the internet were the target population. The sample that was taken to conduct the survey included customers from the Western Province. Hundred banking customers from different banks and diverse localities were surveyed. Out of the 100 respondents, 85 replied to the online questionnaire. The profile of the respondents who participated in the study is demonstrated in Table 1.

Table 1: Respondent’s profile

Characteristics	Categories	N	Percentage
Gender	Male	36	58
	Female	49	42
Age	20 – 30 years old	38	45
	30 – 40 years old	32	38
	More than 40 years old	15	18
Education Level	A/L	21	25
	First Degree	22	26
	Postgraduate Degree	13	15
	Professional Qualification	29	34
Type of the Bank	Government	10	12
	Private	56	66
	Semi-government	19	22

Source: Survey Data, 2022

The conceptual research model is developed based on the E-S-QUAL model, proposed by Parasuraman et al. (2005). The conceptual framework of the study can be illustrated based on that model. The study measures efficiency fulfilment, system availability and privacy of internet banking under 20 dimensions. Explanatory and Confirmatory factor analyses were carried out to achieve the objective of this study.

4. Results and Discussion

4.1 Use of Exploratory Factor Analysis (EFA)

The significance of Bartlett’s Test of Sphericity (Table 2) ratified that the observed correlation matrix is significantly different from the identity matrix, and thus, common factors due to inter-correlation can be investigated.

Table 2: Results of Adequacy Statistics for FA

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.854
Bartlett's Test of Sphericity	Approx. Chi-Square	121.555
	DF	21
	Sig.	0.000
Cronbach’s alpha coefficient		0.931

Source: Survey Data, 2022

Results in table 2 also indicated that the KMO statistic (0.854) is greater than 0.6, confirming that data satisfying sample adequacy for EFA. Cronbach's alpha coefficient of 0.931 confirmed that there is good internal consistency in data. All these results confirmed that the data set is suitable for FA.

4.2 Eigen Analysis for Correlation Matrix Analysis

Eigen analysis for the correlation matrix indicated that four eigenvalues are greater than one. Thus, according to Kaiser's rule (Kaiser, 1960), three factors can be used to explain the observed correlation matrix of twenty variables. However, the variable "The bank's site gives information on command rather than all at once" is not loaded highly in the rotated factor loadings. Thus initial 20 variables were reduced to 19. According to the newly rotated factor analysis using Principal Component Extraction Method (PCF), the initial 19 variables can be reduced to a 3-D system with 93% of the total observed variance.

4.3 Extraction and Rotation of Factors

The factors were extracted using the PCF method and were rotated using Varimax. The corresponding factor loadings are shown in Table 3.

Table 3: Factor Loadings of the 3- Factor Model (PCF & Varimax)

Variables	Factors		
	1	2	3
The site is simple to use	-.078	.975	-.122
requires minimum of information to be input by the customer	-.078	.975	-.122
The speed of login of your account is fast	.572	.812	.114
The site does not confuse you in what you want to do with the pages	.878	.364	.262
The bank's site does not have fine print that is difficult to read and hard to find	.878	.364	.262
The bank's web site makes easy to get anywhere	.018	.973	-.218
The bank's web site enables to complete a transaction quickly	.296	.829.	.096
The bank's web site delivers services when promised	.977	-.147	-.007
Records at bank's web site are always accurate	.673	.150	.716

Bank's web site makes accurate promises about delivery of service	.840	-.397	.176
Bank's web site promptly informs about important situations (payments, balance and etc.)	-.327	-.329	.882
The bank's web site is always available for business	.789	.245	.563
The bank's web site launches and runs right away	.639	-.323	.698
The bank's web site does not crash	.018	.973	-.218
Pages at the bank's web site do not freeze after enter order information	.878	.364	.262
The bank protects information about the web-shopping behavior	.153	-.121	.981
The bank does not share the personal information with other sites	.258	-.406	.876
The bank's web site protects information about the credit card	.258	-.406	.876
The bank's site does not use banner ads with cookies to collect	-.778	-.599	-.052
Extraction Method: Principal Component Analysis.			
Rotation Method: Varimax with Kaiser Normalization.			

a. Rotation converged in 5 iterations.

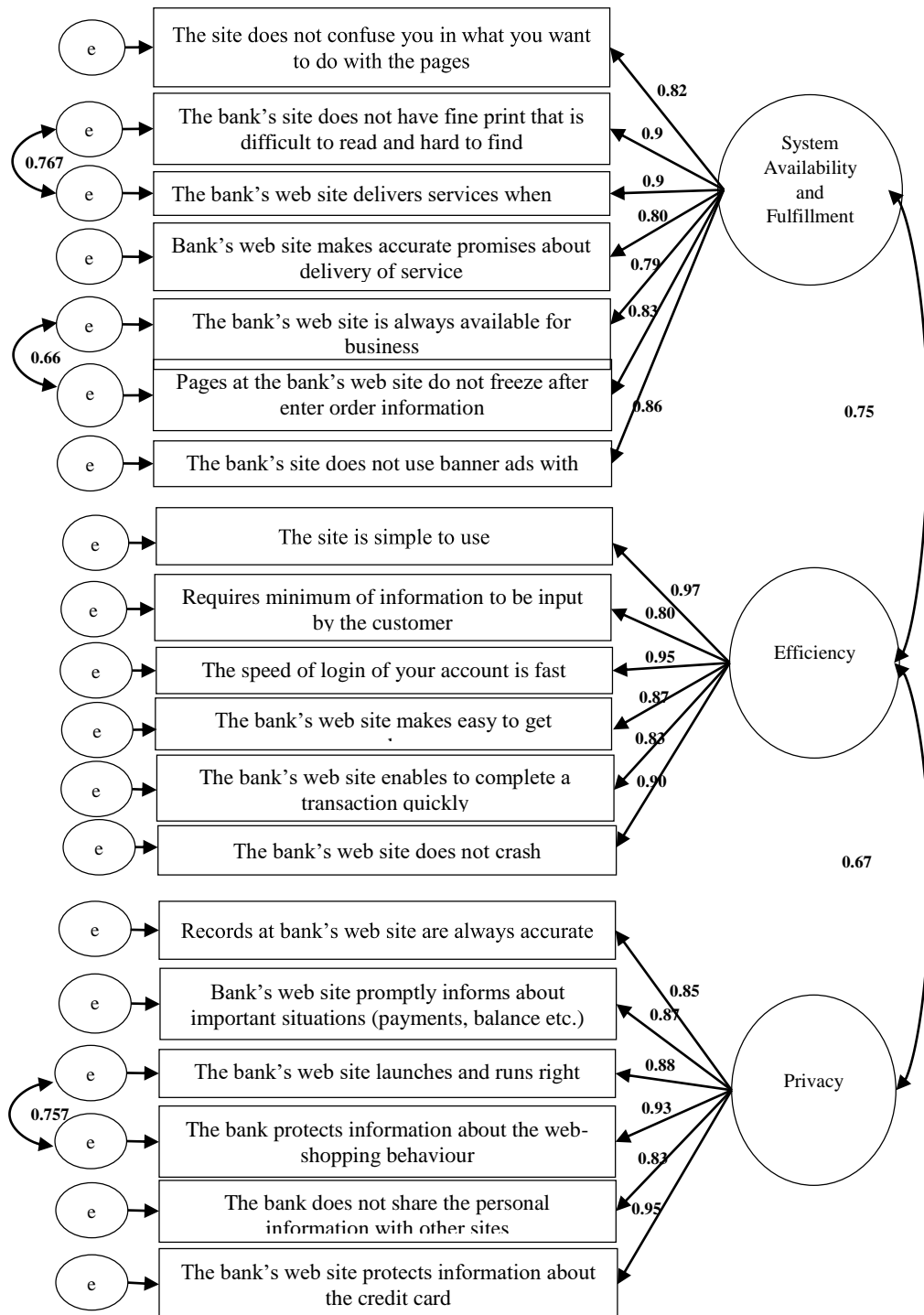
Source: Survey Data, 2022

The three factors were named as, “system availability and fulfillment”, “efficiency” and “privacy”.

4.4 Confirmatory Factor Analysis (CFA)

In order to further justify the structure of the three factors identified using EFA, CFA was also carried out and results are shown in figure 1.

Figure 1: Standardized Parameter Estimates for 2 - Factor CFA



Source: Survey Data, 2022

According to figure 1, all the variables of the three factors indicated high loading values (> 0.8). This justified the validity of the variables selected for the three factors using EFA. The statistics of the model justification are shown in table 4.

4.5 Evaluating Model Fit

The results model chi-square statistic ($\chi^2_8 = 253.369, p = 0.003$) is significant, confirming that the hypothesized model significantly fits the data. As this test is sensitive to sample size various goodness-of-fit indices, have been suggested for the evolution of the model fit and some of the statistical indices generated from SPSS are shown in table 4.

Table 4: Model Fit Summary of Finalized Model

RMSEA	.050
NFI	.798
NNFI (TLI)	.886
CFI	.848
GFI	.745
AGFI	.864
PGFI	.205
PNFI	.486

Source: Survey Data, 2022

RMSEA is close to 0. All other indices in table 4 are higher than the critical value of the corresponding indices confirming that the hypothesized model fits the data adequately.

4.6 Association between Characteristics of Respondents and Three Factors

Table 5: Association between age of the respondents and three extracted factors

Factor	Age			
		20 - 30	30 - 40	More than 40
System availability and fulfilment	N	38	14	14
	%	57.6%	21.2%	21.2%
Efficiency	N	38	14	14
	%	57.6%	21.2%	21.2%
Privacy	N	22	7	10

	%	56.4%	17.9%	25.6%
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Source: Survey Data, 2022

The results of table 5 revealed that when the age of the respondents is increased, the positive perception on the system's availability and fulfilment, efficiency and privacy on internet banking is gradually decreased. This meant that respondents aged 20 to 30 have a high positive perception on the three factors than the other age groups.

Table 6: Association between educational qualification of the respondents and three extracted factors

Factor	Education Qualification				
	A/L	Professional Qualification	First Degree	Postgraduate Degree	
System availability and fulfilment	N	12	24	20	10
	%	18.2%	36.4%	30.3%	15.2%
Efficiency	N	12	24	20	10
	%	18.2%	36.4%	30.3%	15.2%
Privacy	N	7	15	15	2
	%	17.9%	38.5%	38.5%	5.1%

Source: Survey Data, 2022

As mentioned in table 6, respondents with professional qualifications and a first degree have the highest positive perception on the three internet banking factors, respectively. Moreover, respondents with a postgraduate degree have the least positive perception than the other respondents about internet banking.

Table 7: Association between gender of the respondents and three extracted factors

Factor	Gender		
		Male	Female
System availability and fulfilment	N	36	30
	%	54.5%	45.5%
Efficiency	N	36	30
	%	54.5%	45.5%
Privacy	N	9	30
	%	23.1%	76.9%

Source: Survey Data, 2022

According to the results in table 7, male respondents have the highest positive perception on system availability, fulfilment and efficiency of internet

banking. Furthermore, results also revealed that female respondents have the highest positive perception on the privacy of internet banking.

Table 8: Association between Type of bank of the respondents and three extracted factors

Factor	Type of Bank		
		Government	Private
System availability and fulfilment	N	10	56
	%	15.2%	84.8%
Efficiency	N	10	56
	%	15.2%	84.8%
Privacy	N	0	39
	%	0.0%	100.0%

Source: Survey Data, 2022

When considering the type of bank, table 8 indicated that private banks have the highest positive perception on internet banking factors. Also, it is evident that none of the respondents have a positive perception on the privacy of internet banking in government banks.

5. Conclusions

Of the 19 observed variables, three common internet banking factors were identified under the PCF and Varimax orthogonal rotations. CFA further evidence regarding the three factors suggested model concerning the factors identified via EFA. The three factors identified are (i) System availability & fulfilment, (ii) Efficiency, and (iii) Privacy. Further, cross-tabulation revealed that private banks have a high positive perception on service quality of the internet banking than government banks. Moreover, there is no considerable difference between males and females in their perception of system availability, fulfilment and efficiency on internet banking. However, female respondents have a higher positive perception on the internet banking privacy than males. Also, it is evident that respondents with an education level up to A/L and respondents who possessed a postgraduate degree have the least positive perception on internet banking factors, while respondents aged 20-30 have high a positive perception on the three factors.

5.1 Recommendations

Customers always expect economical and time-saving methods. To meet these requirements, banking websites should perform efficiently.

Lower rates and charges are an effective way to attract new customers and satisfy existing customers.

Banks must provide due attention and assistance to help customers adapt and become familiar with internet banking.

Banks should spread awareness and knowledge on internet banking and its benefits among their banking customers.

Banks should cater convenient services for customers of varied income levels by separately identifying the needs and wants of each income strata.

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Factors associated with Fatal Motorcycle Accidents (MAs) in Sri Lanka

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Abstract

Motorcycle accidents (MAs) account for nearly 40% of road traffic accidents (RTA) reported annually in Sri Lanka. The main objective of this research was to identify the risk factors associated with MAs in Sri Lanka. The binary logistic regression analysis is used in this study to predict the relative likelihood of fatal MAs happening against the non-fatal MAs, to determine the risk factors associated with RTAs in Sri Lanka by considering the secondary data from 2013 – 2019. Weekday, dry road surface, clear weather, daylight, a night with improper street lighting, roundabout, road with no junction, age of driver being 40-59, age of the driver being 18-39, age of the driver being less than 18, having no valid license, male, typical working day, typical weekday, and rural area were the variables identified from the binary logistics regression model. These proved to have a significant positive influence on the odd ratio of fatal motorcycle accident occurrences. In order to reduce the number of accidents the severity of injuries, by utilizing signalization, building bridges for pedestrians, establishing pavement tunnels to minimize exposure to moving vehicles are prominently recommended.

Key words: Motorcycle, binary logistic regression, fatal accidents, non-fatal accidents

1. Introduction

Road traffic accidents, though preventable when taken necessary precautions, are a common risk to which anyone, can fall victim (Amarasingha, 2015). The threat of road traffic accidents only seems to be getting bigger and bigger, especially in developing countries, adversely affecting public health and national development. Road traffic accidents or RTAs cause injury and mortality and involve explicit and implicit financial costs (Bai, 2012).

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Pedestrians, cyclists and motorcyclists are often categorized as ‘vulnerable road users.’ The World Health Organization (WHO) (2018) has declared that this category falls victim to over 50% of the deaths caused by RTAs. The WHO has also found out that the national cost of RTAs among most countries is about 3% of their gross domestic product (GDP). Low- and middle-income countries possess nearly 60% of the world’s vehicles, and about 93% of the fatalities caused by RTAs occur in these countries. It has also been found that RTAs are the primary cause of death for children and young adults who fall into the age category of 5-29(WHO, 2018).

Sri Lanka, a developing nation in South Asia, has an upper-middle-income economy. The nation showcases a concerning number of fatalities and damage caused by RTAs (WHO, 2015). WHO data published in 2018 states that the deaths caused by RTAs have risen to 3,554 and amount to 2.80% of total deaths, whereas the age-adjusted death rate is 16.33 per 100,000 individuals (WHO, 2015). According to the police department the monetary, cost of treating those injured in RTAs and the implicit cost of productivity loss triggered by RTAs amount to nearly 130 billion Rupees annually and this cost caused by RTAs is nearly 1.5% of the nation’s GDP (DP, 2018). As per the data of the Police Motor Traffic Division, 8/10 people who are involved in RTAs die, and over 50 citizens are seriously or trivially injured in RTAs every single day. Data from the Census and Statistics report of 2020 indicates that RTAs have become a primary cause of deaths in Sri Lanka. The nation ranks 96th in the world in terms of the age-adjusted death rate (WHO, 2019). In comparison to the other countries in the region, Sri Lanka has the worst road fatality rate. Motorcycles are a common mode of transportation in Sri Lanka, especially among those who belong to the lower middle class, due to the affordability in price, ease of use and convenience in beating the traffic jams in urban areas. According to the Sri Lanka Police traffic statistics, 16,240 motorcycles have been involved in traffic accidents in 2010. Almost 30% of the traffic flow on highways comprises motorbikes. This rise in the usage of motor bikes have invariably led to a rise in motorcycle related RTAs.

This study focused on investigating the risk factors and contributory causes of crashes involving motorcycles using reported data pertaining to accidents obtained from the Sri Lanka Police. Usage of safety helmets has been recognized to be effective in reducing the severity of the injuries caused by RTAs, especially as it prevents injuries to the head. It is mandatory for

motorcycle owners to register their vehicles at the Department of Motor traffic and obtain a valid driver's license to operate the vehicles. In essence, the same set of regulations applicable to all vehicles are also applicable to motorcycles. This popular mode of transportation is often used as a family vehicle to commute to work and even to transport goods.

According to a publication of the WHO in 2002, RTAs have killed nearly 1.2 million people and have injured over 50 million around the world. It was found in an analysis of motor vehicle crashes that over 40% of the individuals who died in RTAs have been operating two-wheeled vehicles. Regardless of the apparent danger, the popularity of motorcycles as a mode of transportation seems to be rising steadily. Recent reports have surfaced that a large portion of motorcycle accident (MA) victims are young males. Further, injuries to the head and lower extremity injuries were commonplace in RTAs that involved motorcycles. The low usage of safety helmets, especially in developing countries, was identified as the key contributor to the alarming number of head injuries.

Considering the above facts, it is clear that MA is one of the most prominent public health issues in the world and in Sri Lanka. MA is a controllable public health problem in Sri Lanka compared to other leading causes of death. It is mandatory to take immediate and effective actions to mitigate this risk. Thus, it is critical to identify the risk factors that influence the MAs in Sri Lanka to curtail this consequential public health problem.

1.1 Problem Statement

Statistics of the Sri Lanka Police reveal that motorcycle accidents are a public health hazard that cause a large number of deaths and injuries. The literature associated with MAs is mainly concerned with accidents resulting in loss of life or serious injuries, inadequacies of public infrastructure, defects in vehicles and other environmental or weather factors beyond human control. It is important to have a substantial understanding of these factors to effectively utilize the funds allocated for minimizing MAs. Further, the importance of establishing traffic safety is highlighted at the United Nations Summit on sustainable development, in their new sustainable development agenda dedicated 2 out of 17 goals to address this matter. For instance, goal 3 stated, "ensure healthy lives and promote wellbeing for all at all ages", where the importance of minimizing RTAs is brought to attention.

Sri Lanka Police puts great emphasis on ensuring that the average user of the transportation system is not at risk of being harmed by motorcycle-related accidents. Moreover, public health personnel are trained in taking actions to minimize the severity of injuries and their occurrence. Multiple explanations have been put forth to explain the obvious reduction in crashes in the recent past, among which rise in the use of safety belts and growth in public funding for infrastructure improvement have been identified as major contributors. However, it is also vital to identify the major risk factors that explicitly affect MAs in Sri Lanka to take immediate action against the loss of human life and mitigate economic and social costs.

Hence the researcher surveys to identify the risk factors associated with MAs using data from 2013 to 2019. Based on the above research question, the derived research objective is to identify the risk factors associated with MAs in Sri Lanka (2013-2019).

1.2 Significance of the Study

The importance of road safety has been acknowledged even by the United Nations at their summit on sustainable development, 2 out of the 17 goals listed in the sustainable development agenda explicitly refer to road safety. For instance, Goal 3 states, “ensure healthy lives and promote wellbeing for all at all ages 2030, provide access to safe, affordable, accessible and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons”. Thus, road traffic accidents are a great threat to public health and require sustainable, effective mechanisms to ensure sustainable prevention. Classification of risk factors of MAs produces increased awareness, improves commitment and ensures informed decision-making across the government and other relevant agencies responsible for ensuring road safety. It helps these organizations to adapt and implement strategies that have been scientifically proven to be effective.

It is also mandatory to recognize and highlight the importance of creating effective partnerships among institutions to ensure road traffic safety. These partnerships should be created horizontally and vertically, in other words, between different levels within the government and between government and non-government organizations. This as a whole includes building partnerships

and collaborations between sectors like public health, transport, finance and even law enforcement.

1.3 Limitations of the Study

This study was designed to analyze and identify the behavior MAs in Sri Lanka from 2013 – 2019. The data source characteristics are limited to some variables. The demographic characteristics of the injured or dead people and drivers were not considered for the study. Further, there can be many attributes that influence MAs, but this study focuses on the attributes which the Sri Lankan Police identify.

2. Literature Review

2.1 MAs in Global Context

Amarasingha (2021), emphasized that middle-income countries showed no reduction in fatality rates from 2013 to 2016. In South-East Asian countries, about 43% of traffic fatalities were due to motorized two-wheelers or three-wheelers involved crashes, 16% were due to non-motorized two-wheeler crashes, and 14% were due to pedestrian crashes. Motorcycle has become an essential vehicle among the people in those countries for commuting or transporting goods because it is an economical and easy mode to be used for short distances. In South-East Asian countries, relative use and ownership of motorcycles or non-motorized two-wheelers are high. For example, 86% of households in Thailand own at least one motorcycle, which is comparatively higher than that in high-income countries.

2.2 MAs in Sri Lankan Context

Traffic data reveal that 1227 people were killed in 2018; as a result of explicitly or implicitly being involved in motorcycle accidents. This was 39.61% of the total fatalities that occurred in that year. Even though motorcycle accidents seem to have become a major public health hazard, the issue has not received due attention, majorly due to lack of information. Little to no attention has been given to the matter both on a national and provincial level. Unlike most public health hazards, motorcycle accidents are preventable by nature. Thus, proper attention must be given to factors that contribute to

motorcycle accidents in order to form effective prevention methods (AlicioDlu, Yalniz, Edkin, & Yilmaz, 2008).

Motorcycles in Sri Lanka usually share the lane with fast-moving vehicles such as cars, buses, and trucks. Motorcycle users are more vulnerable compared to travellers in fast-moving traffic because motorcycles are less visible owing to their smaller size and because they lack protection during a crash. As a result, motorcycle crashes are often reported with severe injuries caused to its users. However, even though the higher risks faced by motorized two-wheeler riders are often documented, the knowledge pertaining to the measures that should be taken to reduce or prevent this high crash risk is incomplete.

There is a positive significant relationship between human factors, environmental factors, legal factors and vehicle factors contributing to motorcycle related accidents. These factors are discussed below.

2.3 Factors identified in Previous Studies

It was revealed in an in-depth investigation of motorcycle accidents that a major proportion of these accidents involved males under 25 years of age (European Association of Motorcycle Manufacturers (EAMM), 2003). A study conducted in Delhi on motorcycle fatalities showed that 93.6% of those involved in motorcycle accidents were males as opposed to female victims, who made up just 6.4%. It was also found that 21- to 30-year-olds (44.67%) were most likely to be involved in motorcycle accidents, and this was followed by the age group 31-40 (27.66%) (Behera, Rautji, Lalwani & Dogra, 2009). Another study also confirmed these findings as it stated that younger males were more likely to be involved in these accidents as opposed to any other demographic group (Ndunguru, 2016).

Training-based interventions are an effective way of minimizing motorcycle accidents. However, imparting the required skills and knowledge in order to ensure maximum control over the vehicle has been found to be a challenging task. The skill set needed to control a motorcycle is much more complicated than the skills needed to handle other vehicles. This is true, especially in an emergency. However, motorcyclists receive relatively less training and supervision when operating on the road. It was found in a scoping study (Elliott et al., 2003) that acknowledging the lack of skill among riders,

improving higher-order cognitive skills among riders and educating the riders on risk levels, rules and knowledge needed for safe riding will improve the safety of motorcyclists. Another study (Hurt et al., 1981) discovered that most riders received no formal training; in fact, 92% of the riders were either self-taught or trained by a friend or family member. In the same study, it was discovered that training motorcyclists reduced or minimized their involvement in accidents and injuries.

The environment and the condition of the road and its surroundings are significant factors that contribute to motorcycle accidents. While factors like road surface, furniture and defects explicitly contribute to accidents, road site vegetation and sudden movement of animals too contribute to the occurrence of accidents. A study (Elliott et al., 2003) discovered that grooving the road surface and raised road markings lead to instability, resulting in accidents.

Accident locations can be classified in numerous ways. It has been found that motorcycle accidents are more likely to occur at intersections as other vehicles violate motorcycle rights of way and other traffic controls. Accidents are also quite commonplace in junctions, and 72% of these accidents happen at T-junctions (McCarthy et al., 2007). Road alignment factor plays a vital role in the occurrence of accidents, and a spot study (McCarthy et al., 2007) found that 70% of the accidents occurred on straight sections of roads. Most accidents that occur in a bend are caused by loss of control. Improved road surfaces also play a role in contributing to the occurrence of accidents. Smooth road surfaces lead to increased speeding, raising the risk of crashes and severity of injury. To conclude, Tanzania (Ndunguru, 2016) revealed that motorcycle accidents were more likely to occur on paved roads than on unpaved ones.

Proper enforcement of licensing and registration for motorcycles could effectively minimize crashes. Proper enforcement of licensing and registration for motorcycles could effectively minimize crashes. While the minimum age limit to obtain a license in Sri Lanka is 18, it was found by Devasurendra (2016) that 29% of the riders could not produce a valid driver's license, and 9% were below 18 years old.

There are two types of licenses issued for motorcycle riders in the UK based on motorcycle type. One is, Light motorcycle license, and another is a standard motorcycle license (Huang, 2004). In Sri Lanka such systems are

absent. Here, the license is issued under three stages. A learner's permit is issued upon completing a written exam conducted by the Motor Traffic Department. Then once the applicant completed a trial, a probation license is issued, and the applicant receives the permanent license within three months. However, the rising levels of accidents reveal that the Motor Traffic Department should consider alternative mechanisms to assess the ability of the applicants to control and operate the motorbikes.

Accident data in Sri Lanka from 2008 to 2012 reveal that nearly 2/3 or 65% of the motorcycles are less than 5 years old and are relatively new vehicles ridden by young riders. Many riders believe that they are competent in performing the necessary repairs on their vehicles as parts are readily available. This leads to poor vehicle conditions and maintenance. Hurt, Ouellet and Thom (1981) revealed that defective maintenance is a leading cause of motorbike accidents.

3. Research Methodology

3.1 Secondary Data

This study consists of panel data of MAs in Sri Lanka, gathered from the Sri Lanka Police Department. All the data are extent the period of 2013- 2019. As mentioned in chapter one, Sri Lanka Police have identified several causes of MAs. The binary logistic regression model will be carried out to derive the risk factors that affect the severity of motorcycle accidents in Sri Lanka as accidents due to various identified factors as mentioned in below mentioned.

3.2 Data Analyzing Methods

The binary logistic regression analysis is used in this study to predict the relative likelihood of fatal MAs against non-fatal MAs to determine the risk factors associated with RTAs in Sri Lanka. The goal of using the binary logistic regression in this study is to describe the association between motorcycle accident severity (fatal/non-fatal) and explanatory variables, which describe the road, human, vehicle, accident, time, and environmental characteristics of MAs by identifying the best-fitted model. Mohammed (2013) claimed that parameters obtained from each explanatory variable in the model is used to estimate the odds ratio. The dependent variable (y) denotes its binary category as 1 and 0.

This study code $y = 1$ (fatal motorcycle accidents) and $y = 0$ (non-fatal motorcycle accidents).

Equation of Logistic regression model is as follows:

$$\pi(x) = p = \frac{e^{\beta_0 + \sum_{i=1}^n \beta_i x_i}}{1 + e^{\sum_{i=1}^n \beta_i x_i}} \quad (1)$$

The logit transformation of the odds dependent variable is;

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{i=1}^n \beta_i x_i \quad (2)$$

Where:

β_0 - Model constant

β_i - Parameter estimates for independent variables

x_i - Independent variables ($i = 1, 2, \dots, n$)

p - Probability ranges from 0 to 1

$\ln\left(\frac{p}{1-p}\right)$: The natural logarithm ranges $-\infty$ to $+\infty$

4. Empirical Findings and Research Analysis

4.1 Association between Severity of Accident and Other Common Factors

In the database, the severity of accident has been classified into fatal and non-fatal, and hence the analysis of the 2-way frequency table was carried out to derive the association between severity of accident and type of the date, condition of the road, light condition of the road, status of weather, the location of the road, age of the vehicle, ownership of the vehicle, gender and age of driver and validity of the license.

As the corresponding p values are less than 5%, it can be concluded with 95% confidence that the sector, day of the week, type of date, alcohol test, condition of the road, light condition of the road, status of weather, the location of the road, age of the vehicle, ownership of the vehicle, gender and age of driver and validity of the license are significantly influential factors on fatal accidents.

The percentage of motorcycle fatal accidents in the rural sector (68%) is significantly higher than that in the urban sector (32%). Rate of occur

motorcycle fatal accidents on weekdays (73.2%) is significantly higher than that on weekend (26.2%) Rate of fatal accidents on typical working days (71.8%) is significantly higher than that on normal weekends (26.5%) and holiday (2.6%). The percentage of motorcycle fatal accidents when alcohol test is not tested (89.2%) is significantly higher than no alcohol or below alcohol limit (9.6%) and over legal limit (1.2%). Rate of fatal motorcycle accidents when the road surface is dry (92.6%) is significantly higher than that when the road is wet (7.4%). The percentage of fatal motorcycle accidents during the daylight (53.3%) is significantly higher than that of during night with improper lighting (40%) as well as than that of during night with good street lighting (6.7%). These results were obtained by comparing two binomial distributions separately. Rate of fatal motorcycle accidents in a clear weather (89.2%) is significantly higher than that in a humid weather (8.7%) and other (2.1%). When the location type is a road without a junction (71.4%), the rate is significantly higher when compared to roads with junctions (19.4%), roundabouts (0.7%) and others (8.5%).

The percentage of fatal accidents when vehicle age is less than 10 years (83.4%) is significantly higher than that when the vehicle age is 10-30 years (16.2%) and greater than 30 years (0.4%). When comparing three binomial distributions separately, the percentage of fatal accidents when the driver's age is between 18 - 40 years (78%) is significantly higher than when the driver's age is between 40 - 60 years (17.5%). Moreover, the percentage of fatal accidents when the driver's age is above 60 years (1.8%) is significantly higher than when driver's age falls between 40 - 60 years. Similarly, the percentage of fatal accidents when the driver's age is less than 18 years (2.7%) is significantly higher than that of when the driver's age is more than 60 years.

4.2 Determine the Risk Factors Associated with MAs

Based on the above statistical analyses carried out separately for each variable, it was found that all other categorical variables have a significant influence on the severity of MAs separately. Thus, in order to find the combined impact from the best set of the independent variables out of all the significant variables, binary logistics regression was carried out under the forward stepwise ward method. The results of the final model are shown in table 1. The significance of the Hosmer and Lemeshow test statistic concludes that the fitted model is significant at 5% level.

The results in table 1 indicate that the variable, day of the week (DW), road surface (RS), weather (W), light condition (LC), location type (LT), vehicle age (VA), vehicle ownership (VO), age of the driver (AD), validity license (VL), gender of the driver (GD), type of day (TD) and sector (S) to predict the outcome variable are significantly associated with severity of accidents when all the variables are taken into consideration simultaneously.

Table 1: Variables in the Equation

Variable	B	S.E.	Wald	d	Sig.	Exp(B)
Weekday (DW)	1.046	.046	520.079	1	.000	2.845
Dry (RS)	4.098	.351	135.990	1	.000	60.232
Other (W)			101.193	2	.000	
Clear (W)	1.525	.152	101.193	1	.000	4.594
Humid (W)	-20.166	1332.42	.000	1	.988	.000
Night – Good (LC)		1	515.245	2	.000	
Daylight (LC)	.357	.057	39.129	1	.000	1.429
Night – Improper (LC)	-.308	.059	26.939	1	.000	.735
Other (LT)			77.368	3	.000	
Roundabout (LT)	-.179	.051	12.179	1	.000	.836
Junction (LT)	.043	.057	.572	1	.449	1.044
Road-No Junction (LT)	.731	.161	20.585	1	.000	2.077
>30 years (VA)			35.356	2	.000	
10 – 30 years (VA)	.118	.221	.284	1	.594	1.125
< 10 years (VA)	.335	.223	2.257	1	.133	1.398
Service (VO)			8.172	2	.017	
Government (VO)	-.205	.206	.993	1	.319	.815
Private (VO)	.510	.336	2.306	1	.129	1.666
>60 years (AD)			566.363	3	.000	
40 – 59 years (AD)	.609	.124	24.204	1	.000	1.838

18 – 39 years (AD)	-.813	.098	68.354	1	.000	.443
<18 years (AD)	-.244	.103	5.628	1	.018	.783
No Valid License (VL)	-2.272	.227	99.928	1	.000	.103
Male (GD)	.107	.032	11.099	1	.001	1.112
Holiday (TD)			312.410	2	.000	
Normal Working Day (TD)	.573	.092	39.099	1	.000	1.774
Normal Weekend (TD)	-.210	.099	4.437	1	.035	.811
Rural (S)	1.155	.031	1358.41	1	.000	3.173
			8			
Constant	-2.415	.555	18.955	1	.000	.089

Source: Survey Data, 2022

Hosmer and Lemeshow Test Statistic: $\chi_8^2 = 115.636$ ($p = .000$)

The overall productivity power of the model is 90.9%. The probability of correctly classifying fatal accidents, given that it is fatal accidents, is .999 against the probability of correctly classifying non-fatal accidents given that it is non-fatal is .155.

The results in table 2 of the Cox & Snell R^2 and Nagelkerke R^2 indicate that the explained variation in the dependent variable based on the model varies from 1.19% to 2.41%. Both statistics indicate the percentage of the variance of the dependent variable is explained by the model. However, various authors have citizen these two indicators.

Table.2: Model Summary

-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2
37870.49	.119	.241

Source: Survey Data, 2022

Thus, the final model for the log odds ratio of fatal accident can be written as:

$$\begin{aligned} \text{Log} \left(\frac{p}{1-p} \right) = & -2.415 + 1.046^{DW.Weekday} + 4.098^{RS.Dry} + 1.525^{W.Clear} \\ & - .357^{LC.Daylight} - .308^{LC.Night Improper} - .179^{LT.Roundabout} \\ & + .731^{LT.Road no Junction} + .609^{AD.40-59 years} \\ & - .813^{AD.18-39 years} - .244^{AD.less than 18 years} \\ & - 2.272^{VL.No valid license} + .107^{GD.Male} \\ & + .573^{TD.Normal working day} - .210^{TD.Normal weekend} \\ & + 1.155^{S.Rural} \end{aligned}$$

Thus, model for odd ratio can be written as:

$$\begin{aligned} \left(\frac{p}{1-p} \right) = & .089 + 2.845 * DW.Weekday + 60.232 * RS.Dry + 4.594 * W.Clear + 1.429 * \\ & LC.Daylight + .735 * LC.Night Improper + .836 * LT.Roundabout + 2.077 * LT.Road no \\ & Junction + 1.838 * AD.40-59 years + .443 * AD.18-39 years + .783 * AD.less than 18 years + \\ & .103 * VL.No valid license + 1.112 * GD.Male + 1.774 * TD.Normal working day + .811 * \\ & TD.Normal weekend + 3.173 * S.Rural \end{aligned}$$

The probability of fatal accidents can be estimates using

$$p = \frac{XX}{(1+XX)} \tag{3}$$

where XX is the,

$$\begin{aligned} & .089 + 2.845 * DW.Weekday + 60.232 * RS.Dry + 4.594 * W.Clear + 1.429 * LC.Daylight + .735 * LC.Night Improper \\ & + .836 * LT.Roundabout + 2.077 * LT.Road no Junction + 1.838 * AD.40-59 years + .443 * AD.18-39 years + \\ & .783 * AD.less than 18 years + .103 * VL.No valid license + 1.112 * GD.Male + 1.774 * TD.Normal Weekend \\ e & + 3.173 * S.Rural \end{aligned}$$

The model (2) indicates that variables weekday, dry road surface, clear weather, daylight, nights with improper street lighting, roundabout, road with no junction, age of driver 40 to 59 years old, age of driver 18 to 39 years old, age of driver less than 18 years old, no valid license, male, normal working day, normal weekend and rural area significantly influence positively on the odd ratio of happening fatal motorcycle accidents.

Using the equation (2) the following conclusions can be made,

The odds of fatal motorcycle accidents happening on a weekday is 2.845 times higher than what occurs on a weekend when all other variables in the model are fixed.

The odds of fatal motorcycle accidents happening on a dry road surface is 60.232 times higher than that it occurs in wet road surface when all the other variables are fixed.

The odds of happening motorcycle fatal accidents in clear weather is 4.594 times higher than what occurs in a humid weather when all other variables are fixed.

The odds of fatal motorcycle accidents happening during daylight is 1.429 times higher than what occurs during the night with good street lighting when all the other variables are fixed.

The odds of fatal motorcycle accidents happening in roads with no any junction is 2.077 times higher what occurs in other location types when all the other variables are fixed.

The odds of fatal motorcycle accidents happening when the age of the driver is between 40 to 59 is 1.838 times higher than when the age of the driver is more than 60 years old when all the other variables are fixed.

The odds of fatal motorcycle accidents happening among male are 1.112 times higher than that of among females when all the other variables are fixed.

The odds of motorcycle fatal accidents occurring during a normal working day is 1.774 times higher than during the holidays when all other variables are fixed.

The odds of motorcycle fatal accidents occurring in rural area is 3.173 times higher than in urban areas when all other variables are fixed.

5. Conclusions, Recommendations & Suggestions

A major proportion of fatal motorcycle accidents (68%) happened in rural areas. 73.2% of the accidents occurred on weekdays considered normal working days. Nearly 90% of the motorcyclists had not done the alcohol test. A similar proportion (92.6%) of the MAs occurred on dry surfaces and 53.8% occurred the during daytime. 71.4% of the accidents occurred on roads that did not have a junction. 83.4% of the vehicles involved in crashes were less

than 10 years old. 99.3% of these new vehicles were privately owned. Out of the drivers, 76% were males and aged 18-40 with a valid license (97%).

Weekday, dry road surface, clear weather, daylight, a night with improper street lighting, roundabout, road with no junction, age of driver being 40-59, age of the driver being 18-39, age of the driver being less than 18, having no valid license, male, normal working day, normal weekday, rural area were the variables identified from the binary logistics regression model. These proved to have a significant positive influence on the odd ratio of fatal motorcycle accident occurrences.

5.1 Recommendations

1. Pedestrian fatalities and injuries can be prevented by utilizing signalization, building bridges for pedestrians and establishing pavement tunnels to minimize exposure to moving vehicles.
2. Establishment of active signage systems that automatically detect pedestrian movement and warn pedestrians through lighting and other signaling of possible danger.
3. Establishing a separate lane for motorcycles and highlighting the presence of them through wearing prominent upper-torso garments and leaving the headlamp on during daytime.
4. Establishment of interconnected brake systems and developing advance training programmes for cyclists.
5. Maintenance of high collision concentration zones and hazardous roads.

5.2 Suggestions

1. Strict adherence to lane driving and the proper use of signals by drivers.
2. Hold programmes that emphasize on the importance of seatbelt usage and maintaining vigilance when driving.
3. Ensuring that the motor bicycle is in proper functioning condition. Not only the engine and breaks must be checked, but due maintenance should also be done for tires, headlamps, gear and signals.
4. Encourage the habit of checking the bike before using for possible defects.
5. Avoid tailgating and be at least 4 seconds away from the vehicle in the front. Further, have an escape route in mind.

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