Exchange Rate Risk and International Equity Portfolio Diversification: A South African Investor's Perspective

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By

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Abstract

This paper examines the impact of foreign exchange rate risk on the expected return of a South African investor's portfolio. A GJR-GARCH based Value at Risk (VaR) model was used to compute the upside and downside risk measures. Data sample of ten emerging stock markets were utilized: from 1 January 2000 to 6 March 2019. The tails of negative and positive asset returns were modelled with the help of the generalized Pareto distribution (GPD) method in order to separate left tail risk from right tail risk. Our findings reveal that international diversification substantially enhances the South African investor's portfolio return, with a noticeable yield increase in China, Brazil, Argentina, Mexico, and Russia. Furthermore, the Singaporean dollar and Chinese Yuan are found to have a negative impact on the portfolio return, while the rest of the currencies have a positive impact on the portfolio return. Also, we found that exchange rate risk is underestimated when using the variance-covariance method as it fails to capture the swing movement of currency in the minimum- value at risk optimization.

Keywords: *International Diversification, Exchange Rate Risk, Portfolio Selection, Value at Risk*

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1. Introduction

The fall of Bretton Woods's system in 1971, known as Nixon shock, led to the dissolution of the fixed exchange rate system that was adopted in 1944 and the introduction of a flexible exchange rate system. Currencies around the world have become considerably more volatile. South Africa, which adopted a floating exchange rate regime in March 1995, has also experienced currency volatility over the years. However, managing exchange rate risk began to capture attention after the 1994 Latin American crisis and the Asian currency crisis of 1997.

After the 2007 global financial crisis, coupled with the Marikana strikes, South African investors have experienced a significant increase in financial risks: particularly currency risk as volatility has increased in recent years across major currencies. Many South African companies such as Sasol, MTN group, Steinhoff international, Remgro, and Naspers involve in international business need to model their exposure to foreign exchange rate risk.

Foreign exchange market is unique in terms of its liquidity, trading volume, market capitalization and the heterogeneity of market participants. According to the Bank for International Settlements (BIS) data, the average daily turnover of foreign exchange markets around the world on September 2018 was $6.64 trillion. Such turnover is created by a large variety of market participants such as international equity investors. In their search for higher gains through international diversification, many portfolio managers are facing foreign exchange exposure. This exchange rate exposure affects the portfolio value and the long-run portfolio return in many ways such as portfolio performance. Therefore, it is very important for South African investors who seek to construct a well-diversified portfolio to quantify and manage their exposure to foreign exchange risk.

Currency volatility has triggered exchange rate risk to be considered as one of the major issues in international portfolio diversification. In this regard, Kabundi and Mwamba (2012) show that South African investors are faced with serious exchange rate risk in their search for benefits from international diversification. It is vital for fund managers to have knowledge of exchange rate fluctuations when seeking for optimal portfolio. Abidin et al. (2004) argue that higher returns with lower risk are likely to occur when diversifying internationally if the currencies are less volatile. They also claim that a stable currency has a positive effect that results in international portfolio diversification reaping higher returns and portraying a lower risk profile. Therefore, controlling currency volatility and exchange rate fluctuations are key issues in portfolio management: this study will look at this as its major contribution.

This study employs the VaR model, developed using GARCH technique to investigate the effect of exchange rate risk on international portfolio diversification. The VaR is incorporated into the model to capture the maximum loss that South African investors have to be prepared to incur during the holding period of foreign assets in their portfolio with a given confidence level. The advantage of this methodology over the one used in Kabundi and Mwanba (2012) based on the genetic algorithm is that we incorporate exchange rate risk in the construction of the investor's portfolio expected return. Using sample data for ten emerging stock markets running from 1 January 2000 through 06 March 2019, the conditional volatility estimation using the GJR-GARCH (1, 1) model shows that these stock markets are prone to the leverage effect. In other words, bad news has a bigger impact than good news on the volatility of different currencies.

Considering the impact of bad news on volatility during a period of extreme events in these markets, we then use the GPD method to separate positive residuals from negative residuals to compute the upside risk and downside risk measures separately. The results show that the bad news likelihood in the stock of emerging markets has a more devastating impact on exchange rate volatility than equivalent good news. The likelihood of market swinging to the recession is very large. Thereafter we calculate the market risk with the above-developed model. Our backtesting results show that the developed model is able to predict extreme losses effectively.

We analyze the impact of exchange rate risk on the portfolio, the result shows that Singaporean dollar and Chinese Yuan have negative impacts on the portfolio with a statistical significance of Chinese Yuan while other currencies have a positive impact on the portfolio return. We also find that improving the Shape parameter of the generalised Pareto distribution improves the tail risk of VaR and reduces the portfolio risk in international diversification return. Therefore, a South African investor in order to maximize his/her investment taking into account exchange rate risk had to put more weight in the stock market with a positive impact on the portfolio. All in all, the most significant finding in this paper is that international diversification substantially enhances the South African investor's portfolio return, with a noticeable yield, increased in China, Brazil, Argentina, Mexico, and Russia.

These results are unique, although some studies such as Biger (1979), Chummun (2017) Kang et al. (2016), Kabundi and Mwamba (2012), Kiani (2011), Grubel (1968), Eun and Resnick (1988), Chummun and Bisschoff (2014), and Jun et al. (2003) have analyzed international portfolio diversification from the perspective of one country investor, most of these studies have not taken into account the exchange rate risk when assessing the benefit from international diversification in an emerging market. The rest of the paper is structured as follows: Section two provides the literature review, section three focuses on the methodology, section four presents the data description and empirical results and, finally, Section five offers a conclusion to the study, as well as some recommendations for policy and future studies.

2. Literature Review

Foreign exchange rate risk refers to the likelihood that the exchange rate will move against the position held by an investor such that the value of the investment is reduced (see Madura, 2011). Many studies have explored the role played by foreign exchange risks on the behaviour of financial markets. Academics and researchers in the field of financial economics have since focused on the benefits and threats of international diversification on the risk-return position for investors.

Among these studies, Adler and Dumas (1984) use simple linear regression to investigate the relationship between exchange rate fluctuations and assets returns. They find that exchange rate has a direct effect on asset returns. Similarly, Kang et al. (2016) find that the exchange rate exposure has a substantial impact on asset returns. Hauser and Levy (1991) argue that foreign exchange rate is more volatile than stock prices, and foreign stocks are positively correlated with exchange rate risk. Kaplanis and Schaefer (1991) state that exchange rate risk may erode the benefits of international diversification, while Akdogan (1996) argue that benefits from portfolio diversification in an emerging market cannot be improved by hedging exchange rate risk.

However, Hauser et al. (1994) show that exchange rate risk plays an important role in emerging markets, and the presence of negative correlation between stock and currency prices can lead to a decrease in the stock volatility. Fidora et al. (2007) show that exchange rate risk accounts for 20% of home bias equity. Contrary to Hauser et al (1994), Horobeţ and Ilie (2010), argue that exchange rate volatility is not an additional factor for the volatility of Central and Eastern Europe (CEE) markets when returns are denominated in US dollars. However, exchange rate risk is a positive contributor to the portfolio, and its impact is higher in turbulent times, such as during the 2007-2008 financial crisis. Horobet and Ilie (2010) also show that currency risk lowers the correlation between the US and CEE markets during the period of financial crises. Choi (1989) also points out the possibility that foreign investment is affected by exchange rate risk. They argue that exchange rate risk and diversification affect international corporate investment in a significant way. In contrast, Biger (1979) argues that in the context of an international portfolio, exchange rate risk matters much less than would be expected.

According to Kabundi and Mwamba (2012), and Eun and Resnick (1988) exchange rate risk plays an important role in determining international portfolio returns, hence choosing an appropriate exchange rate risk methodology that can assess exchange rate risk in emerging markets is one of the key points of this study. In fact, emerging markets differ from developed markets, in that the latter often have some financial instruments to hedge currency exposure such as swaps, futures forward and options contracts, to name a few, while the former has little hedging tools. Therefore, managing exchange rate risk becomes important for international investors in emerging markets.

It has been widely acknowledge by several researchers, such as Culp et al. (1998), Horobet and Ilie (2010), Chummun (2017), Al Janabi (2005, 2006a), Ibragimov (2009), Dowd (2015) and Engle and Manganelli (2001), that VaR models are key tools in effectively measuring exchange rate risk. Culp et al. (1998), exploring the application of VaR for asset managers with particular attention on the importance of VaR for multi-currency asset allocations, point out that VaR can be adapted for multi-currency asset allocations as a statistical measurement and estimation tool for market risk in the long-term. In a similar study designed to emphasize the role played by VaR in multi-currency asset diversification, Al Janabi (2008) acknowledges that VaR is a robust quantitative measure and procedure tool that can be used in equity portfolios combined with foreign exchange portfolios to measure the portfolio risk in emerging markets accurately. Ibragimov (2009) similarly acknowledges that VaR analysis is one of the only approaches to portfolio choice and riskiness comparisons that do not impose restrictions on heavy-tailedness of risk. Dowd (2015), and Engle and Manganelli (2004) also argue that VaR analysis is the most important tool to assess portfolio risk.

As one of the objectives of this study is to assess the impact of exchange rate risk on international portfolio diversification in emerging markets, it is important to select the most suitable VaR methodology.

Danielsson and De Vries (2000) conclude that historical simulation (HS) performs better than the variance-covariance method, while Rejeb et al. (2012), in comparing four VaR simulation methods for the Tunisian foreign exchange market, find that VaR based on the variance-covariance is the most appropriate method. In addition, Semper and Clemente (2003) point out that the VaR-based on autoregressive conditional heteroskedasticity (ARCH) performs better in the assessment of the foreign exchange risk of the portfolio than the VaR methodology used by J.P Morgan RiskMetrics (1994).

Given the above-mentioned literature on risk measurement approaches that widely acknowledge VaR as an important tool in measuring portfolio risk, this study, therefore, will make of the VaR estimates based GJR-GARCH models, to capture the exchange risk effect on international equity diversification. VaR is able to combine all the risk in each individual market together into a single number that is an appropriate indicator of the overall level of risk when dealing with assets from different markets. This study will also utilize the extreme value theory (EVT) in the form of a generalized Pareto distribution (GPD) to compute downside and upside tail risk measure, and analyze the tail loss distribution of exchange rate risk.

In this regard, Wang et al. (2010) argue that a VaR-based on EVT reflects the real market risk. Rufino and De Guia (2011) compare EVT based VaR.Ramazan and Faruk (2004) use daily stock markets to investigate the performance of VaR models and points out that the EVT based VaR estimates are more accurate at higher quantiles.

3. Methodology

3.1. Exchange rate risk and portfolio diversification

South African investors holding investment positions in foreign equity markets use the Rand as their base currency. The rate of appreciation or depreciation of the SA Rand against foreign currency here referred to as the exchange rate risk, is expressed as follows:

$$fex_{it} = \left(\frac{X_{it}^{f} - X_{it}^{s}}{X_{it}^{s}}\right) \qquad (1)$$

where X_{it}^{f} is the forward exchange rate of the South African Rand against foreign currency, and X_{it}^{s} is the spot exchange rate of the South African Rand against a foreign currency.

The expected portfolio return from investing in the i^{th} international emerging market is the combination of the expected return of the asset and the exchange rate risk for that country. We express it as follows:

$$E(r_i) = E(r_{i,t}) + E(fex_{it}) \qquad (2)$$

where $E(r_i)$ is the expected return in market i, $E(r_{i,t})$ is the expected return on a specific market i at time t and $E(fex_{it})$ is the expected exchange rate in market i at time t.

The variance of the total portfolio (P) with weight W_i can be written in matrix notation as follows:

$$Var(P) = W^T A \Sigma_X A^T W + W^T \Sigma_e W \qquad (3)$$

In this paper, we consider that investors are risk-averse with parameter α representing the degree of risk appetite. The portfolio diversification model is mathematically formulated by quadratic programming (QP) optimization problem as follows:

$$MinVar(P) = \frac{\alpha}{2} W^T A \Sigma_X A^T W + W^T \Sigma_e W$$

$$s/t \begin{cases} \sum W_i = 1 \\ \sum W_i \mu_T \geq \mu^* \\ W_i \geq 0 \end{cases} \qquad (4)$$

where α is the degree of risk appetite, μ is the return target and σ is the variance-covariance matrix of the portfolio returns while $\mu_T = \mu + \mu^*$ is the mean of the portfolio (P) and W_i is the weight allocated to each stock market.

3.2- GJR-GARCH estimation

To achieve proper strategies for managing market risk, the present paper develops the methodology that allows one to compute the VaR estimates for individual stock markets and testing the performance of the model using backtesting. The presence of the leverage effect in the model led us to apply the asymmetric GARCH model with a skewed student-t (sstd) innovation that best fits the data. The GJR-GARCH (1, 1) with sstd distribution is formulated as follows:

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_t^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \gamma_i I_{t-i} \varepsilon_{t-i}^2 \qquad (5)$$

where $I_{t-i} = \begin{cases} 1 & if \quad \varepsilon_{t-i} < 0 \\ 0 & if \quad \varepsilon_{t-i} \geq 0 \end{cases}$

where I_{t-i} is a strict white noise process and $I_t \sim N(0,1)$; $\sigma_{i,t}^2$ is the conditional variance of $Y_{i,t}$ over time,t.

3.3 GPD parameter estimates

Let $X_m = max(x_1; x_2 \dots x_m)$ be a series of losses, let F be the distribution function of losses. Since in this study we are interested in losses that exceed a given threshold ϑ. We define the distribution function of excess losses $Y_t = x_i - \frac{\vartheta}{x_i} > \vartheta$ as follows:

$$F_\vartheta(y) = P_r\left(x - \vartheta \leq \frac{y}{x_t} > \vartheta\right)$$
$$= \frac{P_r(\vartheta < x_t \leq \vartheta + y)}{P_r(x_t > \vartheta)} \quad (6)$$
$$= \frac{F(y+\vartheta) - F(\vartheta)}{1 - F(\vartheta)}$$

The threshold will be chosen in such a way that the limit theorem applies in order to avoid biased estimates due to bias-variance tradeoff. To overcome this problem, we first plot the mean excess function (MEF) which is a linear function of the threshold ϑ for the generalized Pareto distributions. If the MEF is a straight line, therefore our threshold is the most appropriate for the model. We follow Dowd (2005) who define MEF as follows:

$$MEF = \mathrm{e}(\vartheta) = E\left(x - \frac{\vartheta}{x} > \vartheta\right) = \frac{\sigma + \xi\vartheta}{1 - \xi} \quad (7)$$

The generalized Pareto distributions (GPD) function is given as follows:

$$G_{\xi,\beta(\vartheta)}(x) = \begin{cases} 1 - (1 + \xi(\frac{x}{\beta(\vartheta)})^{-1/\xi} & if \quad \xi \neq 0 \\ 1 - exp(-x/\beta(\vartheta)) & if \quad \xi = 0 \end{cases} \quad (8)$$

where β is the scale and ξ is the shape parameter or tail index.

We prefer the GPD approximation in this study over the generalized extreme value (GEV) because the GPD can deal with asymmetries in the tails.

3.4 VaR computation

To overcome the shortcomings of excess kurtosis and skewness, this paper employs the VaR-based on GJR-GARCH, which has the capability to take into account the asymmetry in the conditional variance.

The following formula is used to compute the conditional VaR for a single market.

$$VaR(\alpha)_t = \sigma_t F^{-1}(\alpha) \quad (9)$$

The value at risk (VaR) at time t given the confidence level $(1 - \alpha)$ is given for downside (d) and upside (u) as follows:

$$\begin{cases} VaR_{\alpha,t}^d = & -\mu_t - \sigma_t^2 \tau_{u,d}(\alpha) \\ VaR_{\alpha,t}^u = & \mu_t + \sigma_t^2 \tau_{u,d}(1 - \alpha) \end{cases} \quad (10)$$

The expected shortfall is given as follows:

$$ES(\alpha) = VaR(\alpha) + E(Y - \frac{VaR(\alpha)}{Y} > VaR(\alpha)) \quad (11)$$

where $F^{-1}(\alpha)$ is the distribution of the data, σ_t is the volatility of a single index at a time t and α is the confidence level.

3.5 Backtesting

For robustness, we employ both the unconditional coverage test (UCT) and conditional coverage test to check the validity of our model. Jorion (2007) defines backtesting as a formal statistical test constructed to verify if the actual trading losses are in line with the forecast losses. Virdi (2011) points out that an accurate VaR model should satisfy both the unconditional coverage test (UCT) and conditional coverage test (CCT).

UCT determines whether the observed frequency of exceptions is consistent with the frequency of expected exceptions, whereas conditional coverage test (also known as the Christoffersen's interval forecast test) tests not only the proportion of failure but also the independence of exceptions. If the model is accurate, then an exception today should not depend on whether or not an exception occurred on the previous day.

The UCT is based on the likelihood ratio test statistic as follows:

$$LR_{POF} = -2Log\left[\frac{(1-P)^{T-x}P^{x}}{(1-\frac{x}{T})^{T-x}(\frac{x}{T})^{x}}\right] \tag{12}$$

The statistical probability distribution of the unconditional coverage test follows a binomial distribution as follows:

$$P(x) = \binom{n}{x} P^{x}(1-P)^{n-x} \tag{13}$$

where x represents the number of exceptions, P is the probability of an exception for a given confidence level and n is the number of trials. In this case study, the number of trails is 250 trading days in a year.

The likelihood ratio is asymptotically chi-squared distributed with one degree of freedom; we reject the null hypothesis if the likelihood ratio value exceeds the critical value of the chi-square distribution for a given confidence level.

The conditional coverage test developed by Chrisoffersen (1998) does not focus only on the independence of the exception but also on the proportion of failure. The VaR model is accurate if the joint test fails to reject the null hypothesis, and we conclude that exceptions today do not depend on whether or not exceptions occurred on the previous day. The test statistic for independence of exception use the following likelihood ratio:

$$LR_{joint} = LR_{POF} + LR_{ind} \tag{14}$$

The indicator value takes the following range:

$$I_t = \begin{cases} 1 & exception \\ 0 & no\ exception \end{cases} \tag{15}$$

4. Data and Empirical Results

This study makes use of the daily exchange rate data from Thomson Reuters for ten stock markets: Malaysia, Philippines, South Africa, Brazil, China, Russia, India, Argentina, Mexico, and Singapore. Data cover the period from January 2000 to 06 March 2019. The daily spot exchange rate of the South African Rand against the currency of the country where the SA investors hold a position in, as well as a forward daily exchange rate of the South Africa Rand against the foreign currency, being used in the analysis. The countries are selected for this study on the basis of data availability. In order to calculate the returns on the portfolio, we gathered daily closing prices of the stock indices for each of the ten countries in their respective currencies.

4.1 Descriptive statistics

Table 1 below displays descriptive statistics of the equity returns. Seven markets in the portfolio exhibit a negative skewness of the underlying empirical distribution of stock returns. In these markets, South African investors will expect small gains with less extreme losses. MERVAL, ALSI, and PSEI reveal a large downside risk with positive skewness, hence small losses and a few extreme gains. The selected markets show positive excess kurtosis, meaning the distribution of underlying assets is leptokurtic with fat tails and less risk of extreme outcomes.

Table 1: **Descriptive statistics of daily returns**

	nobs	Minimum	Maximum	Mean	Variance	Stdev	Skewness	Kurtosis	Jarque-Ber
ALSI	5002	-16.715	11.328	0.055	2.331	1.527	0.026	5.917	7305.410**
BOVESPA	5002	-10.534	11.261	0.049	2.270	1.507	-0.082	3.302	2281.279**
SHANGHAI	5002	-9.346	9.401	0.011	2.304	1.518	-0.344	5.398	6179.423**
MICEX	5002	-19.543	24.592	0.074	4.086	2.021	-0.115	14.420	43389.39
SENSEX	5002	-13.039	11.484	0.049	1.810	1.345	-0.681	8.045	13890.190
MERVAL	5002	-17.223	47.180	0.153	5.929	2.435	2.017	41.258	358477.30
SINGA	5002	-8.838	5.953	- 0.001	1.134	1.065	-0.347	5.792	7099.607**
KLCI	5002	-8.942	4.501	0.016	0.588	0.767	-0.757	9.710	20148.850
PSEI	5002	-12.170	16.687	0.031	1.527	1.236	0.086	13.031	35433.720
MEXBOL	5002	-8.978	7.303	0.050	1.417	1.191	-0.049	3.559	2645.074**

Note:*ALSI (South Africa); BOVESPA (Brazil); SENSEX (India); KLCI (Malaysia); MEXBOL (Mexico); PSEI (Philippines); SHANGHAI (China); MICEX (Russia); MERVAL (Argentina); SINGA (Singapore).*

The results presented in table 1 show that the Argentine equity index (MERVAL) has the highest returns (15.3%), while the Singaporean (SINGA) market has the lowest returns (1%). Russian and Argentine equity markets prove to be more volatile than other stock markets: they experience the highest standard deviations (2.02) and (2.43) respectively. This is also supported by the large range of disparity in these two markets. Malaysia's stock (KLCI) has the smallest standard deviation, hence it is the least volatile market, implying low risk. This can be reinforced by the small range and can be explained theoretically by the fact that the Malaysian central bank applies a fixed exchange rate system against the US dollar. Any investors who wish to invest in Malaysia would benefit from the fixed exchange rate system that is in place. The Malaysian stock market is less risky compared to other stock markets with flexible exchange rates system. Returns in the sample are not normally distributed, as evidenced by the value of kurtosis, which is greater than three for all markets. The residual series are not normally distributed as suggested by Jacque-Bera statistics that are all significant.

4.2 GJR-GARCH Results

Table (2) reports the estimated parameters of the mean equation and variance equation of the GJR-GARCH (1-1) model applied to daily returns in each market. All parameters in the variance equation are mostly positive and found to be significant at the 5% confidence level. The coefficient of beta implies that volatility that occurs in previous periods is positively transmitted into volatility of the current period in all markets under study. The parameter gamma represents the ARCH effect and is positive for all stock markets. The log-likelihood and AIC show that the GJR-GARCH (1, 1) model with sstd innovation found to be the best model to capture the volatility behaviour of the equity returns in the selected market. We also notice that the autoregressive coefficient is negative in SHANGHAI, PSEI, SENSEX, KLCI, and MEXBOL indicating that returns of the previous period have a negative impact on the volatility of the current period in these markets. Table 2 conveys an implausible message that higher return in the past reduces the current volatility in most of the stock markets and are prone to leverage effect. Thus, bad news affects the volatility in the currency market more than good news.

Table 2: GJR-GARCH (1, 1) parameter estimates

	Mean equation			**Variance equation**				
	μ	a_1	a_2	ω	α_1	β_1	γ_1	AIC
ALSI	0.053 (0.014)***	0.887 (0.02)***	-0.912 (0.024)***	0.038 (0.010)***	0.052 (0.009)***	0.915 (0.012)***	0.032 (0.011)***	3.4
BOVESPA	0.044 (0.016)***	0.607 (0.10)***	-0.663 (0.09)***	0.032 (0.01)***	0.034 (0.009)***	0.929 (0.013)***	0.040 (0.011)***	3.4
SHANGHAI	0.008 (0.016)	-0.721 (0.357)**	0.732 (0.351)**	0.018 (0.006)***	0.055 (0.010)***	0.929 (0.011)***	0.028 (0.012)**	3.2
MICEX	0.067 (0.06)***	0.994 (0.001)***	-0.993 (0.000)***	0.045 (0.009)***	0.074 (0.010)***	0.897 (0.010)***	0.034 (0.013)***	3.7
SENSEX	0.061 (0.01)***	-0.273 (0.203)	0.331 (0.198)	0.028 (0.005)***	0.051 (0.009)***	0.880 (0.011)***	0.098 (0.016)***	2.9
MERVAL	0.120 (0.027)***	0.376 (0.316)	-0.308 (0.325)	0.112 (0.025)***	0.077 (0.013)***	0.879 (0.013)***	0.059 (0.018)***	4.0
SINGA	0.011 (0.010)	0.131 (0.164)	-0.182 (0.162)	0.008 (0.002)***	0.031 (0.008)***	0.930 (0.009)***	0.056 (0.010)***	2.5
KLCI	0.017 (0.008)	-0.099 (0.226)	0.170 (0.224)	0.007 (0.014)***	0.055 (0.014)***	0.915 (0.019)***	0.035 (0.013)**	1.9
PSEI	0.032 (0.015)**	-0.252 (0.177)	0.305 (0.174)	0.109 (0.019)***	0.083 (0.015)***	0.798 (0.023)***	0.086 (0.021)**	3.0
MEXBOL	0.042 (0.013)***	-0.547 (0.328)	0.567 (0.323)***	0.018 (0.005)***	0.035 (0.009)***	0.920 (0.012)***	0.062 (0.012)***	2.9

***NB**: *** indicates significance at 1 %level,** indicates significance level at 5% level,* indicates significance at 10% level, in parentheses is the standard error.*

4.2 Fitting the Data to generalized Pareto distributions

We model the tail behaviour of assets returns by making use of the GPD for the upper and lower tail in order to account for the impact that bad news has on volatility during extreme events. The results show that the shape parameters for both upside and downside tail distribution increase as the confidence interval increases. Furthermore, we find that the left tail distribution exhibits negative shape parameters in SHANGHAI indicating that extreme losses are likely to be high in this market.

Table 3: GPD Parameter estimates Lower tails and Upper tail

		Left tail parameter estimates			Right tail Parameter estimates		
		99%	95%	97.5%	99%	95%	97.5%
ALSI	Shape: ξ	0.402	0.192	0.267	0.243	0.223	0.344
	Scale: β	0.816	0.735	0.741	1.100	0.800	0.793
	Log Likelihood	46.775	188.641	97.83	72.331	233.39	129.134
BOVESPA	Shape: ξ	0.333	0.109	0.241	0.195	0.085	0.296
	Scale: β	0.816	0.844	0.756	1.046	0.921	0.700
	Log Likelihood	64.407	268.81	126.935	59.566	234.67	111.842
SHANGHAI	Shape: ξ	-0.296	-0.131	-0.131	0.132	0.181	0.189
	Scale: β	2.047	1.760	1.760	1.261	0.893	1.006
	Log Likelihood	119.28	228.063	228.063	69.632	263.039	148.355
MICEX	Shape: ξ	0.232	0.177	0.103	0.406	0.259	0.351
	Scale: β	1.799	1.632	2.029	1.680	1.290	1.342
	Log Likelihood	132.856	421.985	260.824	96.310	349.756	199.21
SENSEX	Shape: ξ	0.197	0.082	0.133	0.085	0.288	0.138
	Scale: β	1.064	1.141	1.039	1.209	0.665	0.979
	Log Likelihood	112.082	358.645	246.049	59.972	209.939	137.561
MERVAL	Shape: ξ	-0.081	0.160	0.141	0.630	0.273	0.422
	Scale: β	3.101	1.770	2.107	1.692	1.641	1.543
	Log Likelihood	102.506	384.267	198.155	105.698	406.973	215.424
SINGA	Shape: ξ	0.142	0.098	0.181	-0.315	0.144	0.039
	Scale: β	0.951	0.832	0.763	1.396	0.708	0.911
	Log Likelihood	72.099	267.07	160.548	50.924	195.96	119.243
MEXBOL	Shape: ξ	0.036	0.051	0.045	-0.067	0.080	-0.049

	Scale: β	0.918	0.825	0.870	1.026	0.831	1.047
	Log Likelihood	45.630	216.647	120.65	46.991	203.439	119.577
KLCI	Shape: ξ	0.062	0.280	0.369	-0.153	0.140	0.017
	Scale: β	1.144	0.49	0.512	0.725	0.460	0.599
	Log Likelihood	56.299	134.511	91.941	25.751	86.465	59.701
PSEI	Shape: ξ	0.169	0.267	0.191	0.442	0.207	0.324
	Scale: β	1.119	0.75	0.952	0.741	0.655	0.629
	Log Likelihood	85.957	229.312	143.959	54.911	187.708	101.651

We realize that, on the left tail, the distribution of SHANGHAI presents a thin tail at 99%; 95%; and 97.5% quantiles, therefore, modelling this distribution with the normal distribution would underestimate the extreme losses in this market. The majority of the markets have positive shape parameters at both left and right tail, an indication of the presence of fat tails.

4.3 VaR Results

We compute VaR and ES for both downside and upside risk. The results are reported in table 4.

Table 4: Downside and Upside risk measure

		Upside Risk measure			**Downside Risk measure**		
	Confidence Interval	**99%**	**95%**	**97.5%**	**99%**	**95%**	**97.5%**
SINGA	VaR	2.849	-0.082	1.364	3.850	2.277	2.911
	ES	3.910	1.683	2.782	5.126	3.292	4.030
ALSI	VaR	4.009	2.515	3.088	4.303	3.155	3.560
	ES	5.492	3.517	4.274	5.923	4.003	4.681
SHANGHAI	VaR	3.994	2.161	2.903	6.050	3.101	4.545
	ES	5.453	3.339	4.195	7.154	4.878	5.992
BOVESPA	VaR	3.691	2.258	2.820	4.534	3.186	3.679
	ES	4.981	3.200	3.899	6.159	4.135	4.876
SENSEX	VaR	3.392	1.583	2.332	5.031	3.138	3.880
	ES	4.708	2.730	3.548	6.740	4.383	5.307
MICEX	VaR	5.280	3.295	3.994	7.446	4.353	5.545
	ES	8.113	4.767	5.946	10.446	6.417	7.970
MEXBOL	VaR	3.291	1.544	2.320	3.921	2.451	3.074

	ES	4.254	2.617	3.344	4.896	3.371	4.017
MERVAL	VaR	6.396	4.706	5.233	8.431	3.376	5.635
	ES	10.918	6.346	7.771	11.146	6.474	8.562
KLCI	VaR	2.047	0.718	1.331	2.790	0.967	1.730
	ES	2.678	1.526	2.058	4.059	2.115	2.929
PSEI	VaR	2.986	2.148	2.438	4.212	2.349	3.090
	ES	4.293	2.789	3.309	5.806	3.562	4.454

The result shows that for all markets in the portfolio, as the confidence interval increase the ES estimates increases and are greater than VaR at all points.

4.4 Out of sample VaR forecast and backtesting

We split the data sample into two: the training sample (75%) and testing sample (25%). We conduct the forecast of daily VaR and test the ability of our model in the out- sample space. The results are reported in Table 5 below. The unconditional test results show that the likelihood ratio statistic fails to reject the null hypothesis of the correct number of exceptions. Therefore, we conclude that the VaR model based on skewed t-student distribution GJR-GARCH works well for the sample at 99%, 95% and 97.5% except for MICEX market which at 95% the UCT test rejects the null hypothesis. On the other hand, the conditional coverage test result of our VaR model used to test for the accuracy of the model fails to reject the null hypothesis at all confidence interval except for MICEX and MEXBOL at 97,5% where the correct exceptions and independence of failure is not rejected. Our findings show that the VaR model is accurate in nine emerging stock markets at all confidence levels, an indication that our market risk model produces reliable VaR estimates in the out-sample.

However, the joint test rejects the null hypothesis in two stock markets at 95%, namely Mexico (MEXBOL) and Russia (MICEX), which implies that the VaR model has clustered exceptions in the aforementioned markets, hence, is inaccurate and fails to take into account the correlation and the volatility in these markets. Therefore, the conditional coverage test is inaccurate for these markets; in other words, today's exception in these markets depends on whether or not exceptions occurred on previous days. As the VaR model used in this study is developed to assess the impact of the exchange rate in emerging stock markets, the presence of clustered exceptions in the VaR model in the Russian and Mexican stock markets and the inaccuracy of the joint test may be due to the fact that these countries in practice are less open to international investors. Therefore the volatility of exchange rate does not really affect the stock market returns.

Table 5: Unconditional and conditional backtesting results in out-sample

Backtesting test	ALSI	BOVESPA	SHANGHAI	SENSEX	MICEX	MERVAL	MEXBOL	KLCI	PSEI	SINGA
Confidence level 1%										
Expected exceptions	30	30	30	30	30	30	30	30	30	30
Actual exceptions	23	20	32	25	22	27	33	25	22	23
Actual %	0.8	0.7	1.1	0.8	0.7	0.9	1.1	0.8	0.7	0.8
UCT										
Test Statistic	1.804	3.828	0.129	0.899	2.385	0.318	0.289	0.899	2.385	1.804
Critical value	6.635	6.635	6.635	6.635	6.635	6.635	6.635	6.635	6.635	6.635
P-Value	0.179	0.05	0.719	0.343	0.122	0.573	0.591	0.343	0.122	0.179
Reject null hypothesis	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
CCT										
Test statistic	2.159	4.097	0.819	2.505	2.71	0.808	1.023	1.319	2.71	2.159
Critical Value	9.21	9.21	9.21	9.21	9.21	9.21	9.21	9.21	9.21	9.21
P-Value	0.34	0.129	0.664	0.286	0.258	0.668	0.6	0.517	0.258	0.34
Reject null hypothesis?	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Confidence level 5%										
Expected exceptions	150.1	150.1	150.1	150.1	150.1	150.1	150.1	150.1	150.1	150.1
Actual exceptions	131	147	153	130	119	153	132	152	146	134
Actual %	4.4	4.9	5.1	4.3	4	5.1	4.4	5.1	4.9	4.5
UCT										
Test Statistic	2.668	0.068	0.059	2.962	7.279	0.059	2.391	0.025	0.119	1.883
Critical value	3.841	3.841	3.841	3.841	3.841	3.841	3.841	3.841	3.841	3.841
P-Value	0.102	0.795	0.809	0.085	0.007	0.809	0.122	0.874	0.73	0.17

Reject null hypothesis	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO
CCT										
Test statistic	4.354	3.069	0.064	3.532	8.052	2.311	8.855	2.378	3.269	2.063
Critical Value	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991
P-Value	0.113	0.216	0.968	0.171	0.018	0.315	0.012	0.305	0.195	0.356
Reject null hypothesis?	NO	NO	NO	NO	YES	NO	YES	NO	NO	NO
Confidence level 2.5%										
Expected exceptions	75	75	75	75	75	75	75	75	75	75
Actual exceptions	75	62	88	56	59	81	70	65	64	61
Actual %	2.5	2.1	2.9	1.9	2	2.7	2.3	2.2	2.1	2
UCT										
Test Statistic	0	2.472	2.173	5.43	3.795	0.472	0.356	1.445	1.755	2.879
Critical value	5.024	5.024	5.024	5.024	5.024	5.024	5.024	5.024	5.024	5.024
P-Value	0.995	0.116	0.14	0.02	0.051	0.492	0.551	0.229	0.185	0.09
Reject null hypothesis	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO
CCT										
Test statistic	0.009	2.833	3.497	5.432	3.819	0.489	3.7	1.582	5.314	3.291
Critical Value	7.378	7.378	7.378	7.378	7.378	7.378	7.378	7.378	7.378	7.378
P-Value	0.996	0.243	0.174	0.066	0.148	0.783	0.157	0.453	0.07	0.193
Reject null hypothesis?	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Note: backtesting hypothesis for unconditional coverage test (UCT) and conditional coverage test (CCT). ***Null hypothesis (UCT):*** *Correct exceedance;* ***Null hypothesis (CCT):*** *Correct exceedance & independent*

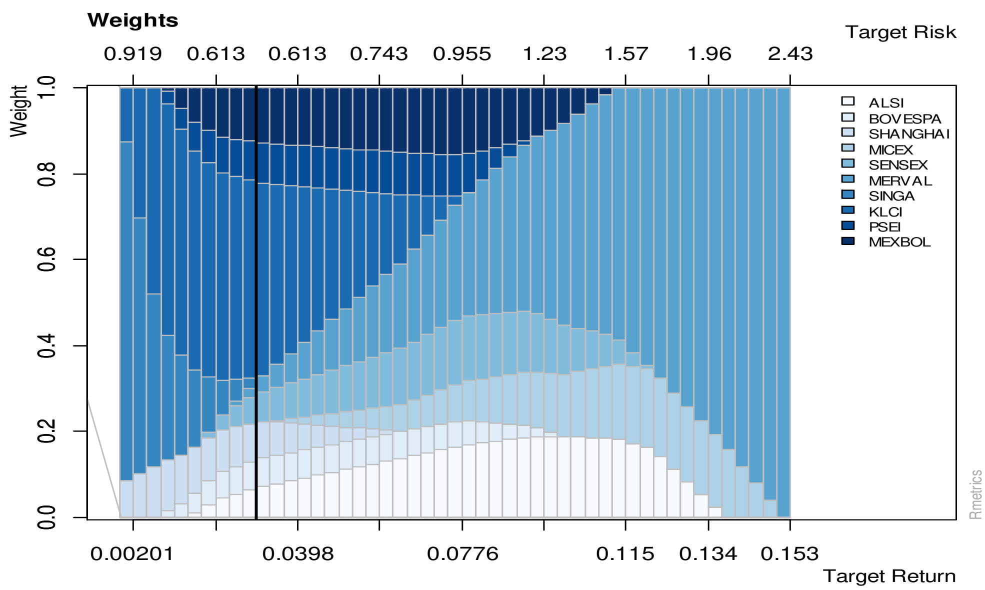
4.5 Value at Risk and portfolio diversification

We employ two types of optimization: Minimum-VaR optimization and Mean-Variance optimization. we also compute the portfolio VaR. Table 6 below reports the tangency portfolio (CET) accumulation wealth and the portfolio VaR of the two types of optimizations. The main findings from the two optimization techniques are that diversification substantially reduces portfolio risk and enhances the portfolio return yield with a noticeable yield increased in China, Brazil, Argentina, Mexico, India, and Russia. For the South African risk-averse investor, more weight is allocated to Argentina, Mexico, and India. The portfolio risk measure (variance) is also greater than the individual stock market risk. At 1% confidence, diversification provides benefit for South African investors in the following market: Argentina, China, Russia, Brazil, India, Mexico and Philippines where the portfolio value at risk is less than individual VaR in those market.

Table 6: Optimal portfolio diversification and value at risk

	Optimization: Min-VaR			Optimization: Mean-Variance MV			Portfolio Value at Risk		
	return	weight	Min risk	return	weight	Min risk	VaR 99%	VaR 95%	VaR 97.5%
ALSI	0.054	0.103	0.109	0.054	0.156	0.115	3.701	2.306	2.872
BOVESPA	0.049	0.064	0.065	0.049	0.059	0.039	3.765	2.433	3.014
SHANGHAI	0.011	0.044	0.027	0.011	0.000	0.000	3.094	2.265	1.655
MICEX	0.073	0.028	0.035	0.073	0.080	0.079	5.907	2.849	4.154
SENSEX	0.048	0.1	0.100	0.048	0.146	0.095	4.076	2.148	2.980
KLCI	0.015	0.309	0.203	0.015	0.054	0.011	2.002	1.124	1.526
PSEI	0.031	0.096	0.079	0.031	0.097	0.040	3.279	1.838	2.389
SINGA	-0.001	0.00	0.00	-0.001	0.154	0.000	4.898	2.398	3.270
MEXBOL	0.049	0.139	0.140	0.049	0.000	0.103	3.240	1.828	2.399
MERVAL	0.153	0.114	0.238	0.153	0.250	0.514	6.382	3.235	4.524
Portfolio	0.048		0.993	0.048		1.334	8.837	2.215	3.004

The result also shows that the Malaysian stock market does not yield any diversification benefits for the South African based investor. An indication that exchange rate risk reduces the expected return and stock market risk. We base this conclusion on the fact that Malaysia is the only stock market in the portfolio that has a fixed exchange rate regime. Therefore, South African investors should target the stock market with flexible exchange rates.



4.6 Exchange rate risk and portfolio diversification.

Table 7 exhibits the impact of exchange rate risk on portfolio returns. The result shows that Singaporean dollar and Chinese yuan have a negative impact on the portfolio return, while the rest of the currencies have a positive and significant impact on portfolio returns. The regression analysis shows that the currency exchange risk negatively affects the individual markets, although combining them tends to enhance the portfolio returns. This leads to the conclusion that diversification enhances portfolio return yield.

Table 7: Betas exchange rate risk of Rand against foreign currencies

Historical returns	fex_{zar}	fex_{sing}	fex_{arg}	fex_{roub}	fex_{cny}	fex_{phi}	fex_{peso}	fex_{ring}	fex_{rup}	fex_{real}
ALSI	0.120***	-0.024***	0.007	-0.042***	-0.010***	-0.017**	-0.008	-0.022***	-0.020***	-0.016
SHANGHAI	-0.012	-0.006**	-0.009	-0.016	-0.003***	-0.012***	-0.006	-0.006**	-0.008***	-0.014
BOVESPA	-0.166***	-0.031***	-0.058***	-0.059***	-0.001	-0.014***	-0.112***	-0.013***	-0.014***	-0.254***
SENSEX	0.003	0.003	-0.001	-0.007	0.000	-0.006	-0.005	-0.000	-0.063***	0.012

MICEX	-0.062***	-0.009***	0.006	-0.016**	0.002*	-0.004	-0.009	-0.000	-0.009**	-0.018**
MEXBOL	-0.126***	-0.021***	0.013	-0.012	0.000	0.001	-0.100***	0.002	-0.005	-0.044***
MERVAL	-0.034***	-0.007***	0.030***	-0.035***	-0.001	-0.004	-0.033***	-0.000	-0.013***	-0.052***
KLCI	-0.034	-0.012	0.004	-0.027	-0.003	-0.006	0.020	-0.042***	-0.018	0.018
SINGA	-0.068***	-0.004	-0.017	-0.016	-0.000	-0.036***	-0.010	-0.039***	-0.011	-0.025
PSEI	0.031***	0.011**	0.007	0.022**	0.004***	-0.039***	0.036***	0.006	0.005	0.036***
portfolio	0.031**	-0.000	0.025**	0.0159**	-0.004**	0.008	0.029**	0.006	0.015***	0.025**
R-square	0.182	0.116	0.86	0.082	0.026	0.106	0.225	0.004	0.166	0.278

Note: fex is foreign exchange rate of local currency against South African Rand, sing (Singapore dollar);arg (Argentina peso); roub (Russian rouble); cny (Chinese yuan); phi (Philippines peso); peso (Mexican peso); ring (Malaysian ringgit); rup (Indian rupee); real (Brazilian real)

Our results show the role played by exchange rate risk on international portfolio wealth and indicate that South African investors who seek to maximize their investment, taking into account exchange rate risk have to put more weight in stock markets in Argentina, Mexico, India, and Russia which have positive and significant impacts on the portfolio return . The Malaysian currency improves returns in all the markets as well as the portfolio, but this impact is not significant.

5. Conclusion and Policy Recommendations

The rapid change in global financial markets and the fluctuations of exchange rates have attracted investors' attention. International portfolio seems to be the main focus of multinational firms as well as fund managers who are seeking high returns with a minimum risk. Exchange rate risk has a paramount role to play in international portfolio diversification, where financial assets are dominated in different currencies and are therefore exposed to currency risk. Our findings reveal that foreign exchange rate fluctuations impact portfolio returns with negative effect from the Singaporean dollar and

Chinese yuan. We also noticed that the returns on the previous periods in all markets in the sample have a negative impact on the volatility of the current period. Therefore, these stock markets are prone to the leverage effect, implying that bad news has a greater impact than good news on volatility in the currency market. We also find that increasing the shape parameter of the model tends to improve the performance of the model as well as increasing the fatness of the left tails and skewness significantly reduces the impact of exchange rate impact

Our findings reveal that international diversification substantially enhances the South African investor's portfolio return, with a noticeable yield increase in China, Brazil, Argentina, Mexico, and Russia. In considering the South African investor as a risk-averse investor, we noted that a sustainable and continuous fall in exchange rate may lead to the loss of money through the opportunity risk. The exchange rate risk in some markets feature fat tails and are leptokurtic. Hence the normal VaR underestimated the exchange rate risk. Considering the presence of the fat tails in the distribution of exchange rate risk, we find the GJR-GARCH with skewed student-t distribution as the best performing model in assessing exchange rate risk in international diversification. Based on these findings, we recommend South African investors who intend to maximize their investment taking into account exchange rate risk to place more weight in stock market such as Argentina, Mexico, India, and Russia which have a positive impact on the portfolio.

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