International Equity Diversification between South Africa and its Major Trading Partners

by

Michelle Gounden[1], Ishkaar Jugmohan[2], Jarryd Phillips[3]
Department of Finance and Tax,
University of Cape Town,
Cape Town, South Africa
E-mail: GNDMIC001@myuct.ac.za[1], JGMISH001@myuct.ac.za[2],
PHLJAR001@myuct.ac.za[3]

and

Kanshukan Rajaratnam
Department of Finance and Tax & the African Collaboration for
Quantitative Finance and Risk Research,
University of Cape Town, Private Bag,
Rondebosch 7701, South Africa
E-mail: Kanshukan.rajaratnam@uct.ac.za

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Abstract

This preliminary study analyses share price returns between South Africa and its major trading partners around the world, using weekly data for the period 1 January 2000 to 30 June 2012. Unit Root tests proving non-stationarity of the data enabled the use of GARCH (1:1) modelling. Results show that strong volatility linkages exist between South Africa and Australia, the Netherlands, Germany the United Kingdom and France. Following this, a mean-variance optimal risky portfolio was constructed as theorised by Markowitz. A weighting of 12% in Netherlands AEX and 88% in U.K's FTSE provides an optimal risk-return structure.

Keywords: International Diversification, JSE, South Africa's Major Trading Partners

1. Introduction

This article aims to examine the benefits of international diversification from a South African investor's perspective. Diversification is a technique used to reduce the risk of a portfolio by investing in a variety of assets. The rationale behind international diversification is that foreign securities tend to be less correlated with domestic securities thus increasing the benefits of investing internationally. Diversification benefits are demonstrated by the correlation between returns. Lower correlations mean that investments are affected in different ways by economic events. Extensive research has been performed on the benefits of investing in foreign markets. These studies have demonstrated that international diversification is the most powerful and cost-effective tool for risk reduction. Although a considerable amount of research has been done on foreign economies, little attention has been devoted to international diversification from a South African perspective.

Globalisation and the rapid development of information technology have enabled markets to increase trade phenomenally over the past few decades. Globalisation has further given way for co-movement of stock prices across international markets, exposing local markets to economic turmoil, natural disasters and political instability, amongst other shocks, from foreign markets. This study aims to test for volatility linkages and its implications for portfolio diversification in the context of South Africa and its major trading partners. An optimal weight structure for portfolio diversification will also be provided. South Africa, being ranked in fourth place for its financial market development in the 2011/2012 World Economic Forum's (WEF) Global Competitiveness Index, has set the way for many strengthening foreign trade relations. Whilst the European debt crisis continues and the U.S. market remains frail in its recovery, many investors are looking to the emerging markets for growth (Matola, 2012).

BRIC is an acronym that refers to the emerging markets of Brazil, Russia, India and China, and is widely associated with the transfer of global economic power to these fast-growing economies from the developed countries of the G7 economies (United States of America, United Kingdom, Japan, Italy, France, Germany and Canada). In 2010, South Africa (SA) became a member nation of the alliance and the group was renamed to BRICS. BRICS is the third largest trading group after Europe and Asia and it is estimated that the group will overtake the G7 economies by 2027 (Forooha, 2009). For this reason, this paper includes a specific analysis of the BRIC nations. Other countries that were considered in this analysis include Nigeria, Hong Kong, Japan, Italy, France, Netherlands, Switzerland, Germany, Australia, Saudi Arabia, the United Kingdom (U.K.), the United States of America (U.S.) and Turkey. These countries were chosen based on South African economic data on the largest exports and imports over the past decade (South Africa Online, 2011).

The reasons for international diversification are risk reduction and return enhancement. By investing in foreign assets with low correlation, an investor is best able to achieve this. Differences in political, economic and institutional structures, including psychological factors in some cases, allow a lower correlation of equity across countries relative to within an individual country. Furthermore, business cycles are highly asynchronous across countries. Longin and Solnik (1995), however, found that international diversification tends to be overrated due to the findings that markets tend to move more closely together during periods of high volatility from their study of the October 1987 market crash. In the case of correlation between emerging markets, if the crisis is caused by external factors, the emerging markets tend to experience a prolonged recession relative to developed nations. Solnik and Roulet (2000) further proved that the average correlation of 15 major stock indices with the world market during the period 1971- 1981, has increased by approximately 10%.

With these considerations in mind, we thus look to the specific type of market that is best suited to international diversification. An emerging market, such as South Africa, would obtain greater diversification benefits with markets of developed countries. Emerging and developed markets offer greater differences in political and economic structure and thus would theoretically offer lower correlations. Furthermore, emerging markets tend to have a higher risk allocation for uncertainty, albeit higher returns that are rewarded on the market, whilst developed markets offer stable returns with a more predictable volatility thereby providing the investor with an attractive portfolio. Knowledge of correlation and volatility linkages between stock markets are integral to both investors and policy makers alike. Investors are interested in low correlations for diversification benefits whilst evidence of volatility linkages allow policy makers to understand the inter relations between countries and can thus plan accordingly.

This paper is organised as follows: Section 2 provides an analysis of literature pertinent to the study; Section 3 describes the data used; Section 4 explains the methodologies used in the study and provides an interpretation of the results thereof and finally, Section 5 concludes the study.

2. Literature Review

Since the 1987 global equity markets crash and the 1997 Asian crisis, there has been a surge of studies examining the linkages between international stock markets (Chinzara & Aziakpono, 2009, p. 2). Chinzara & Aziakpono (2009) have completed a study that directly coincides with the purpose of this paper, within a South African context. Their study investigates the return linkages and volatility transmission between SA and the major stock markets of the world. Chinzara & Aziakpono (2009) employ the univariate GARCH and multivariate Autoregressive models thus providing the aspect of volatility in their analysis. The results from the Chinzara & Aziakpono (2009) study show that volatility linkages exist between South Africa and Australia, China and the U.S. for the period 1999-2007. Similar studies conducted in international markets such as China, Vietnam, India, the United Kingdom as well as the emerging eastern Europe all prove direct volatility linkages between the countries and their respective major trading partners (Allen, Amram, & McAlee, 2011; Chang & Su, 2009; Jeyanthi & Annapakiam, 2010; Samouilhan, 2006; Fedorova & Saleem, 2009).

It was further found that volatility was "inherently asymmetric" as was the finding in the Vietnamese market that was analysed by Chang & Su (2009). Chang & Su (2009) pursued a similar model to Chinzara & Aziakpono (2009) when they explored the relationship of Vietnam's stock market with its major trading partners using a Threshold Error Correcting Model (TECM) with a bivariate, asymmetric GARCH. An asymmetric model was utilised after Chang & Su (2009, p. 1280) found that the volatility of the stock market in Vietnam and its trading countries have an asymmetrical effect. Asymmetric GARCH also accounts for leverage effects observed in stock returns. Samouilhan (2006) uses the Exponential GARCH (EGARCH) variant of the asymmetric GARCH models, when evaluating the relationship between international equity markets and the JSE. EGARCH uses a method of conditional variance to model the asymmetric directions of good/bad events based on past trends.

The Capital Asset Pricing Model (CAPM), as pioneered by Sharpe (1964), Lintner (1965), Mossin (1965) and Merton (1973), theorises that investors are rewarded with greater returns as the risk in their portfolio increases. This model rests on the assumption that a constant market variance is required in order to render the CAPM as a valid model. As such, Engle (1982) developed a volatility model, to measure the conditional variance or volatility of the time series data. Standard regression models assume that the residuals of the model are homoskedastic or, constant over time. However, Crouhy & Rockinger (1998) and Sakthivel et al (2012) have shown that volatility clustering is evident in stock price returns. In addition, Bollerslev (1986) proves that volatility evolves over time. Furthermore, studies by Black (1976) and Chang & Su (2009) show that volatility exhibits asymmetric behaviour through a tendency to increase in response to bad news and decline in response to good news. This implies that there is evidence of heteroskedasticity in the data and is intuitive given that some periods tend to be more risky than others which cause the standard errors to be larger in those periods than usual. A test for unit roots in the data conclude trends in the share price returns and imply that heteroskedasticity of residuals in the model exist. A more appropriate model is thus required to account for this, such as the Auto-Regressive Conditional Heteroskedasticity (ARCH) model. ARCH models perform volatility forecasts of stock return data and are generally used when a characteristic variance is suspected in time series data (Goyal, 2000). The use of ARCH does not invalidate the standard ordinary least squares inference, however, ignoring ARCH effects could lead to skew results and weak beta coefficient estimates. To obtain more accurate results, a Generalised ARCH model (GARCH) is used in this study.

3. Data Collection

The data used in this paper are the weekly closing share price series of the composite or all share indices of each country's markets and were obtained from Bloomberg. Composite indices were considered favourable as they are best available indicators of country market performance. Table 1, below, outlines the composite indices used for the analysis.

Table 1 Composite Index of the Analysed Countries

Emerging Markets	
Country	**Index**
South Africa	All Share Index (ALSI)
Brazil	BOVESPA
Russia	MICEX
India	NIFTY
China	Shanghai Composite
Nigeria	NGSE Index
Hong Kong	Hang Seng
Japan	Nikkei 225
Italy	FTSE MIB
France	SBF 120
Netherlands	AEX
Switzerland	SMI
Germany	CDAX
Australia	ASX 200
Saudi Arabia	Tadawul
United Kingdom (U.K.)	FTSE 100
United States of America (U.S.)	S&P 500
Turkey	XU 100

The time frame of the study spans from 1 January 2000 to 30 June 2012. Chatfield notes that "classical methods work quite well when the variation is dominated by a regular linear trend and/or regular seasonality. However, they do not work very well when the trend and/or seasonal effects are changing through time or when successive values of the irregular fluctuations are correlated". The data was subsequently split into recessionary and market recovery periods to capture the specific trends. Table 2, below, specifies the five periods that were analysed in the study.

Table 2 Time Periods Analysed

	Dates	Number of years	Number of Observations	Period Classification
Period 1	1 January 2000- 31 December 2001	2	130	Recession
Period 2	1 January 2002- 31 December 2003	2	103	Recession
Period 3	1 January 2004- 31 December 2007	4	208	Recovery
Period 4	1 January 2008- 31 December 2009	2	103	Recession
Period 5	1 January 2010- 30 June 2012	2.5	103	Recovery

Period 1: Fall of the Dot-com Bubble - The dot-com bubble started in the late 1990's as a result of an investment fad within the internet and related fields sector. The bubble finally peaked in peaked in March 2000 when the markets eventually crashed due to Microsoft being declared as a monopoly in the market in conjunction with the increasingly high interest rates. The attacks against America on September 11 also contributed to the bearish market during this time.

Period 2: Stock Market Downturn of 2002 - Many analysts view this period as a mean reversion following the dot-com bubble burst. Stock exchanges across the U.S., Canada, Asia and Europe experienced a sharp decline in stock prices.

Period 3: Bull Market - During this period, the market eventually took a positive turn and was making a steady recovery from the previous recession.

Period 4: Sub-prime Crisis - The sub-prime crisis began in December 2007 and marked the beginning of the greatest global depression since 1929's Great Depression. The crisis was caused by the housing bubble in America where U.S. mortgage backed securities were marketed at cheap credit rates. Credit rating agencies added to the crisis by posting false ratings on credit providers. The bubble was burst when the Federal Reserve increased interest rates against the market expectation of interest rate cuts. The effect of the crisis had a global presence with many countries facing substantial losses and bankruptcies, in some cases, on their financial markets.

Period 5: Current Market - The current global market is making a tentative recovery and remains largely uncertain with the fear of a double dip recession spurred by decisions made around the Euro, political instability in the middle-east and a slow-down of economic growth in China.

4. Findings and Conclusion

Partial results of this exploratory study are found in the appendix. From the GARCH results, we note the following key findings.

In period 1, characterised by the dot-com bubble which peaked and crashed in March 2000, the U.K., Australia and the Netherlands obtained the highest AIC values, being greater than □5□. The corresponding log likelihood figures for these countries are relatively high in the period which adds weight to the prediction power of the model. Similarly, in period 2, when the markets displayed a downward trend due to mean reversion, the U.K., Germany, France, Italy and the Netherlands displayed best diversification opportunities. The U.K., France, Switzerland, Italy, Hong Kong, and Brazil have the highest AIC values for period 3. Of note, the best fit of the model was attained in this period, which may be attributed to the distribution of the data during the bullish market during this time. Period 3 also accounted for a total of four years of data, which may have made the GARCH model more robust. Interestingly, period 4, denoted by the sub-prime crisis, presented significant AIC values (greater than 4.6) for all countries studied. Upon deeper analysis, countries with AIC values greater than 4.7 were the developed countries in this study, with the exception of India (an emerging market) and Turkey. The results obtained in this period disputes the study conducted by Longin and Solnik , who find that correlations among markets increase during periods of increased volatility. In the current period, which is characterised by an uncertain market, the U.S., France, Australia and the Netherlands provide optimal diversification benefits with AIC's greater than 4.5. Corresponding log likelihood values are relatively weak in comparison to periods 1 and 3. The empirical results found in this study suggest that international diversification benefits for South African investors lie with the U.K., France, Australia and the Netherlands whilst the market is either uncertain or in a downturn. These countries displayed consistently high AIC values during periods 1, 2, 4 and 5. Following the 2008 sub-prime crisis, the U.S. is less correlated with the South African market and displays good diversification benefits in periods 4 and 5.

During the bull market, characterised by period 3, France and Switzerland display extremely low correlations with South Africa and would thus be the investment countries of choice. France is the only country that has a significant AIC value for all five periods which suggests that it is the ultimate source of portfolio diversification regardless of the market condition. As expected, most results show low correlations between South Africa, being an emerging market, and the developed markets. In period 3, however, Brazil has a significant AIC value. Similarly in period 4, India also has a low correlation with the South African market. This could possibly suggest the emergence of investment benefits among members of the BRIC countries.

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Appendix

Table 1: Period 1		
	AIC	**Log-Likelihood**
SA - U.S.	-4.720590	314.199
SA - U.K.	-5.298550	352.055
SA - Turkey	.NaN	294.234
SA - Saudi	-3.799321	246.257
SA - Nigeria	-3.803203	254.11
SA - Japan	-4.199638	280.076
SA - Germany	-4.894380	325.582
SA - France	-4.983402	331.413
SA - Australia	-5.373682	356.976
SA - Switzerland	-4.758877	316.706
SA - Netherlands	-5.047451	335.608
SA - Italy	-4.556464	303.448
SA - Hong Kong	-4.523597	301.296
SA - China	-3.991425	266.438
SA - Russia	-3.796414	251.767
SA - Brazil	-4.804226	319.677
SA - India	-3.797782	251.856

Table 2: Period 2		
	AIC	**Log-Likelihood**
SA - U.S.	-3.575709	192.725
SA - U.K.	-4.148849	222.815
SA - Turkey	-3.603427	194.18
SA - Saudi	-2.924283	155.601
SA - Nigeria	-2.935793	159.129
SA - Japan	-3.251712	175.715
SA - Germany	-4.450621	238.658
SA - France	-4.383801	235.15
SA - Australia	-3.845751	206.902
SA - Switzerland	-3.703440	199.431
SA - Netherlands	-4.462901	239.302
SA - Italy	-4.006271	215.329
SA - Hong Kong	-3.498450	188.669
SA - China	-2.985096	161.718
SA - Russia	-3.672035	197.782
SA - Brazil	-3.907790	210.159
SA - India	-3.286252	177.528

Table 3: Period 3		
	AIC	**Log-Likelihood**
SA - U.S.	-3.440258	366.227
SA - U.K.	-4.189979	444.948
SA - Turkey	-2.963349	316.152
SA - Saudi	-2.660553	277.707
SA - Nigeria	-2.911509	310.708
SA - Japan	-3.268961	348.241
SA - Germany	-3.968979	421.743
SA - France	-4.353885	462.158
SA - Australia	-3.758957	399.691
SA - Switzerland	-4.336178	460.299
SA - Netherlands	-3.971897	422.049
SA - Italy	-4.062520	431.565
SA - Hong Kong	-4.122207	437.832
SA - China	-3.121658	332.774
SA - Russia	-3.692102	392.671
SA - Brazil	-4.122207	437.832
SA - India	-3.833151	407.481

Table 4: Period 4		
	AIC	**Log-Likelihood**
SA - U.S.	-4.741795	253.944
SA - U.K.	-4.879546	261.176
SA - Turkey	-4.658417	249.567
SA - Saudi	-4.644829	248.853
SA - Nigeria	-4.659556	249.627
SA - Japan	-4.750745	254.414
SA - Germany	-4.818303	249.096
SA - France	-4.804314	257.227
SA - Australia	-4.886249	261.528
SA - Switzerland	-4.831114	258.633
SA - Netherlands	-4.839770	259.088
SA - Italy	-4.775215	255.699
SA - Hong Kong	-4.740733	253.888
SA - China	-4.642613	248.737
SA - Russia	-4.678713	250.632
SA - Brazil	-4.666815	250.008
SA - India	-4.763074	255.061

Table 5: Period 5		
	AIC	**Log-Likelihood**
SA - U.S.	-4.596598	246.321
SA - U.K.	-4.381857	235.047
SA - Turkey	-4.126761	221.655
SA - Saudi	No Convergence	220.201
SA - Nigeria	-4.127757	221.707
SA - Japan	-4.110348	220.793
SA - Germany	.NaN	257.961
SA - France	-4.590409	245.996
SA - Australia	-4.598949	246.445
SA - Switzerland	-4.294215	230.446
SA - Netherlands	-4.574265	245.149
SA - Italy	-4.423134	237.215
SA - Hong Kong	-4.256679	228.476
SA - China	-4.094659	221.240761
SA - Russia	-4.247873	228.013
SA - Brazil	-4.141444	222.426
SA - India	-4.272591	229.311