

## Empirical Analysis of Stock Returns and Volatility of the Zimbabwean Stock Markets

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**Abstract:** *The class of generalized autoregressive conditional heteroscedastic (GARCH) models has proved particularly valuable in modelling time series with time varying volatility. These include financial data, which can be particularly heavy tailed. This paper investigates the time-series behavior of stock returns for Zimbabwe stock market. In most cases, higher average returns appear to be associated with a higher level of volatility. Testing the relationship between stock returns and unexpected volatility, the evidence shows that the Industrial Stock Market has significant results whilst the Mining Stock Market shows a different behaviour. A trend analysis of the nominal prices of stocks is done as well as trend analysis of the generated stock returns for both markets. Trend analysis enables the performance of the stock market to be noticed over time. Trend Analysis has favoured the Industrial Stock Market over the Mining Stock Market. The study concludes that there is need to develop the mining sector to attract investors as its growth is showing a downward trend.*

**Key Words:** *stock returns, volatility, Zimbabwe stock markets, asymmetric effect, garch model, archeffects*

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### I. Introduction

Many investors realize that the stock market is a volatile place to invest their money. The daily, quarterly and annual moves can be dramatic, but it is this volatility that also generates the market returns

investors experience. Volatility is a measure of dispersion around the mean or average return of a security. One way to measure volatility is by using the standard deviation, which tells you how tightly the price of a stock is grouped around the mean or moving average (MA). When the prices are tightly bunched together, the standard deviation is small. When the price is spread apart, you have a relatively large standard deviation.

The stock market is a large financial entity that serves many purposes. It allows the public to engage in corporate activity which can suit both investors and companies alike. The economy of a nation further benefits from stock market activity. While the stock market does not always perform well, its core function offers benefits to a society that are not possible without it.

This paper seeks to analyse the stock market volatility of the Zimbabwe Stock Exchange (ZSE). This will be done by analyzing the data from the Mining Index and the Industrial Index and commenting on the trends and behaviour of the data. Performance of the stock exchange strongly reflects the state of the economy. A highly functioning stock market transforms to economic growth. The trends of the two indices shows the performance over time, and reflects the level of growth. All indices in the ZSE have now been adjusted following the base year February 2009, after the collapse of the Zimbabwean Dollar.

According to Chen et al (1986), empirical evidence suggests that, apart from traditional economic forces, stock returns have been analyzed typically by employing time series models. One approach in analysing stocks is through the investigation of time-series patterns and cross correlations of stock returns, and examination of the relationship between stock returns and conditional variance. The main concern is to detect whether there is a predictable pattern associated with stock-return series and this implies a profitable trading rule, rejecting an efficient-market hypothesis. Some studies conclude that not all of the time series of stock returns follow a random-walk process. In cross-country studies, findings provided by Kim and Rogers (1995), Koutmos and Booth (1995), Wei et al. (1995), and Chiang and Jiang (1998) indicate that national stock returns are significantly correlated; and the linkages among international stock markets have grown more interdependent over time.

Another approach of studying stock series is to link the stock returns to risk factors. Stock volatility exhibits a clustering phenomenon, for example, large changes tend to be followed by large changes and small changes tend to be followed by small changes. In modeling this market phenomenon, Autoregressive Conditional Heteroscedasticity (ARCH) and the extension to the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model (Bollerslev, 1986) will be employed. The GARCH(1,1) model appears to be sufficient to describe the volatility evolution of stock-return series. Due to the fact that the GARCH model fails to take into account the asymmetric effect between positive and negative stock returns, the weighted innovation models such as exponential GARCH (Nelson, 1991) and Threshold Autoregressive GARCH or TAR-GARCH model (Glosten et al., 1993, henceforth, GJR; Engle and Ng, 1993; Tsay, 1998) have been advanced. This line of research highlights the asymmetric effect by emphasizing that a negative shock to returns will generate more volatility than a positive shock of equal magnitude.

Despite a substantial amount of empirical research on stock-market behavior, most studies have concentrated on the major developed stock markets. There have been only a few comparable research works devoted to investigation of Zimbabwean Stock Markets. For this reason, we examine time-series behavior of the two Zimbabwe Stock Markets, the Industrial Market and the Mining Market. Particular attention is given to the empirical relationship between stock returns and volatility by employing a GARCH specification.

The volatile behavior of asset returns interacts dynamically with shocks in the rest of world through a contagion effect or other channels of transmission. Hence, the issue of volatility is not only a regional phenomenon, but also an integral part of global risk analysis. To provide more accurate information to aid global portfolio managers in achieving an efficient mean-variance frontier and to provide policy-makers with a more definite basis on which to formulate appropriate risk-management strategy, it is of interest to conduct an empirical investigation on stock-return reaction to risk.

The study uses recent daily and monthly data starting for the multicurrency regime (dollarisation period), February 2009 and focus on the two markets. Second, in addition to examining the relationship between stock returns and the predicted/unpredicted volatility (French et al., 1987), asymmetries in the time-varying volatility process are investigated. Finally, to check the empirical findings, diagnostic methods proposed by Engle and Ng (1993) are employed to assess the robustness of the model.

## **II. The Data And Basic Statistics**

The data used in this study are the monthly stock-price indexes for Mining Index and Industrial Index, for the Zimbabwean Stock Market from January 2010 through December 2013. Daily stock prices for the Industrial index are also used for the period February 2009 through to December 2013.

Daily and Monthly stock returns are obtained by taking the logarithmic difference of the daily/monthly stock index times 100. That is;

$$R_t = \log P_t - \log P_{t-1} \dots\dots\dots (eqn 1)$$

To provide a general understanding of the nature of each market return in Zimbabwe, summary statistics are presented. The statistics include mean return, standard deviation, skewness, excess kurtosis, autocorrelation, and Ljung-Box Q(12) value for the returns and squared returns.

French et al. (1987) provide a direct test of the relationship between excess returns and volatility. They document that market excess returns are positively related to the expected volatility of stock returns, but negatively related to the unexpected volatility of stock returns. The relationship between stock returns and standard deviations for each country are tested by using the following equations for expected and unexpected monthly standard deviations;

$$R_t = \alpha_0 + \alpha_1 \sigma_t^e + \varepsilon_t \dots \dots \dots (eqn 2)$$

$$R_t = \alpha_0 + \alpha_1 \sigma_t^u + \varepsilon_t \dots \dots \dots (eqn 3)$$

The daily/monthly variance of returns is calculated by the sum of the squared daily/monthly returns plus twice the sum of the products of adjacent returns. The calculation is given by;

$$\sigma_{it}^2 = \sum_{i=1}^N R_{it}^2 + 2 \sum_{i=1}^{N-1} R_{it} R_{i,t+1} \dots \dots \dots (eqn 4)$$

GARCH (1,1) in mean model will also be presented. A key criticism in studying the relationship between stock returns and volatility is that this specification fails to account for time-varying risk (Merton, 1980). To address the issue of heteroscedasticity, a number of empirical studies have shown that the volatility series exhibits clustering phenomenon, i.e., large changes tend to be followed by large changes and small changes tend to be followed by small changes. Recent empirical evidence indicates that the impact of news may be “asymmetric.” Specifically, good news and bad news may have different impacts on predicting future volatility.

Data for daily industrial index have been obtained from the Econet Wireless website, Econet Wireless is one of the listed company on the Zimbabwe Stock Exchange. Monthly stocks for the Mining index and Industrial index have been obtained from African Financials website, the company traces on daily happenings in the stock market. Monthly data have also been checked against Quarterly Digest statistics from the Zimstats.

Eviews econometric software will be used for data analysis and modelling. The software is user friendly and gives the required statistics for the data analysis.

### III. Data Analysis Of The Zimbabwe Stock Market

This section will analyse trends of stocks over time and these will be presented in line graphs that enables the direction of flow to be seen.

#### 3.1 Monthly Mining Index (February 2009 – December 2013)

The following diagram shows the trend of the Mining Index for the period February 2009 to December 2013.

**Figure 1: Minings Index Feb 2009 –December 2013**

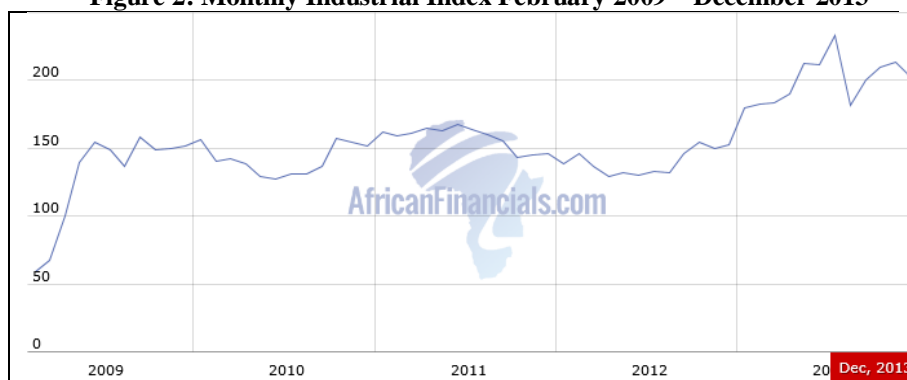


The trend shown above, shows that the index initially rise in the first months or year when the stock market was resuscitated, and later the index has been falling, until a rise was experienced in the mid 2010, and the downward trend continues to the current date. This shows that returns are low and the mining sector is not performing well and corrective measures should be taken to avoid the collapse of the sector.

### 3.2 Monthly Industrial Index (February 2009 – December 2013)

Below is also a diagram that shows the trend of the Industrial index since February 2009.

Figure 2: Monthly Industrial Index February 2009 – December 2013

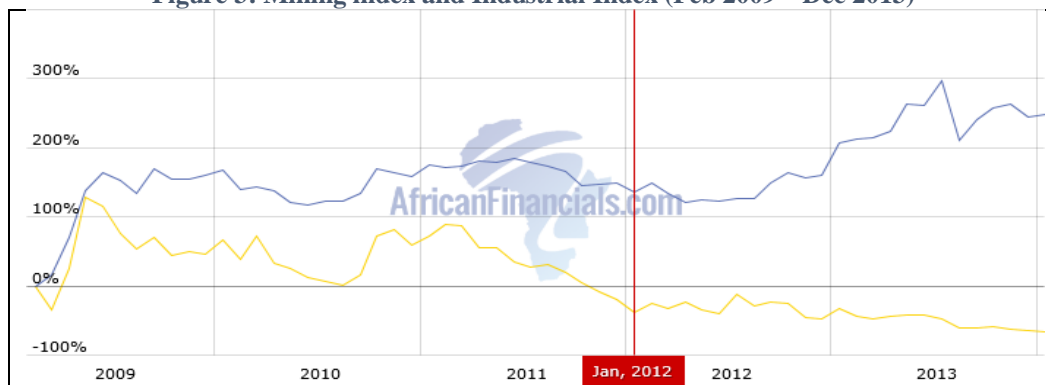


The industrial index has shown a rising trend since February 2009, and thereby stabilising until 2012 when it started rising to the year end of 2013. This shows that the sector has been experiencing some stability for a number of years, and there is attained growth for year 2013.

### 3.3 Mining and Industrial Trends

To provide a comparison between the performance of Mining index and Industrial index, a graph on the same axis is drawn. This is shown by the graph below.

Figure 3: Mining index and Industrial Index (Feb 2009 – Dec 2013)

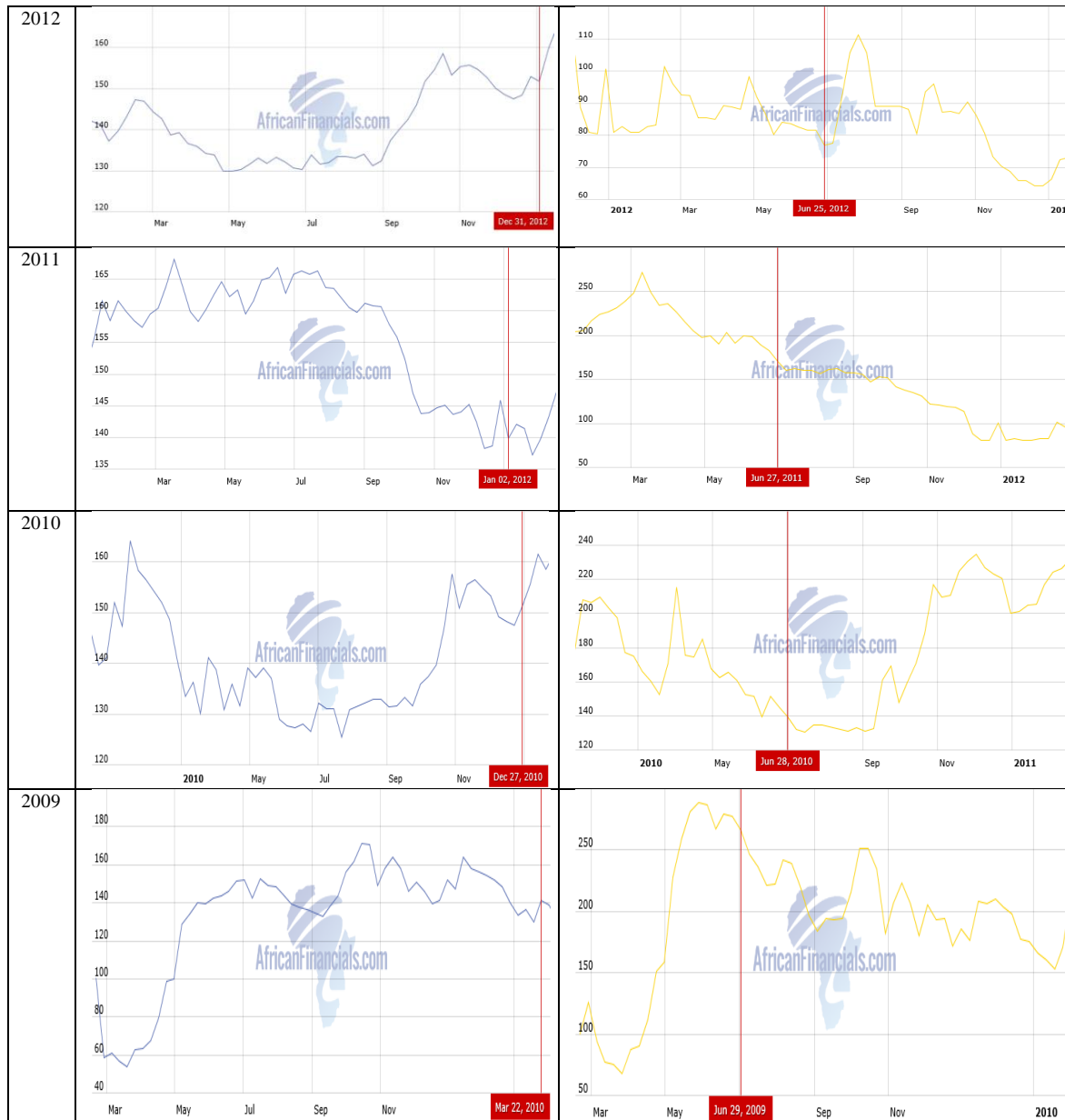


The above diagram shows the trends for the two indices. It shows that whilst the industry is revolving the mining sector continues to face some challenges and hence continued underperformance.

### 3.4 Year by Year Trend Analysis

The following diagram shows the year by year trend analysis of the two indices. This helps us to conclude and see what each year has managed to contribute to the growth of the stock market. Each year has its own challenges and achievements, though there is meaningful linkages between them.

Year	Industrial Index	Minings Index
2013		



According to the above trends, the Industrial index have risen during the 2013 year, whilst it experienced the worst downward trend in 2011. 2009 and 2012 there was rising trends. The Mining Index has been declining in all the years and 2010 shows a little recovery which was later wiped away.

3.5 Stock Market Monthly Data

Period		Industrial Index	Mining Index	US\$Millions Market Capitalization	Turnover Value US\$Millions	Turnover Volume Millions
2010	January	156.52	209.81	3 973.42	32.45	741.27
	February	140.37	175.08	3 552.36	29.61	444.25
	March	142.37	216.85	3 595.94	39.63	1 119.13
	April	139.01	167.90	3 490.29	29.41	543.68
	May	129.40	159.28	3 242.68	30.87	1 221.95
	June	127.46	143.08	3 193.16	29.23	451.74
	July	130.92	134.87	3 296.95	28.64	269.29
	August	130.92	127.64	3 299.90	35.74	415.51
	September	137.04	145.65	3 418.04	25.96	351.22
	October	157.71	217.07	3 978.29	29.70	390.77
	November	154.60	230.61	3 942.85	53.47	427.68
	December	151.27	200.40	3 884.49	26.86	523.58
2011	January	161.10	216.82	4 131.82	32.55	302.74
	February	159.04	239.08	4 101.65	47.48	239.52
	March	160.65	237.18	4 156.32	36.38	349.98
	April	164.66	197.48	4 222.67	35.50	357.06
	May	163.37	197.47	4 191.38	28.90	474.99
	June	167.18	171.32	4 267.50	42.91	377.73
	July	163.69	160.17	4 172.70	51.31	619.77
	August	160.53	164.52	4 105.93	42.39	3 618.01
	September	155.82	152.42	3 984.47	34.94	304.27
	October	143.58	131.75	3 656.59	38.62	545.15
	November	144.98	115.47	3 677.61	41.32	309.88
	December	145.86	100.70	3 689.69	45.21	410.91
2012	January	138.52	79.09	3 489.84	55.79	383.22
	February	146.03	95.39	3 696.60	30.99	225.22
	March	136.76	85.01	3 458.10	32.19	190.46
	April	129.55	97.15	3 303.40	31.75	439.19
	May	132.03	83.73	3 351.20	41.56	524.68
	June	131.96	75.70	3 341.46	65.20	486.52
	July	132.92	112.12	3 445.93	47.09	295.28
	August	132.27	89.04	3 434.00	23.00	194.49
	September	146.00	96.00	3 882.80	30.23	287.78
	October	154.47	93.66	4 033.76	37.86	204.49
	November	150.16	68.74	3 890.90	26.72	157.99

Note: 1. Market capitalization is the issued share capital multiply by the closing price of each counter  
 2. Value of turnover is the value of shares bought or sold in a month  
 3. Volume of turnover is the number of shares bought or sold in a month  
 4. The base year for the stock indices is February 19, 2009

Source: Zimbabwe Stock Exchange

The table above shows the Stock Market data, the two indices and the turnover that has been reaped. However, there is a lot of fluctuations and hence investment predictability is very difficult. The sectors have shown great instability and hence this affects economic growth.

3.6 Market Returns

Nominal trend analysis is good for decision making and for taking effective action. However, it is crucial to analyse the stock market returns for effective investment decisions. Stock market returns are calculated using the formula;

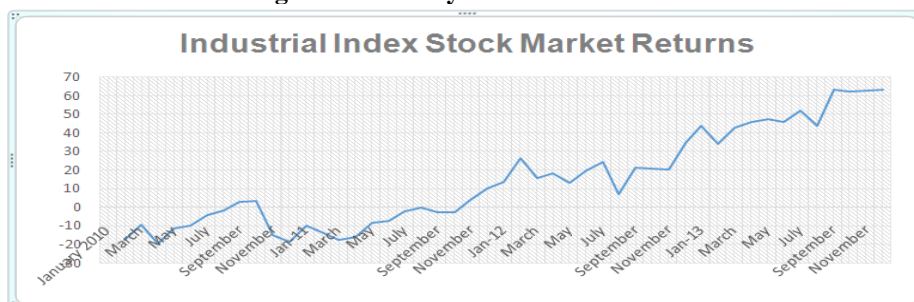
$$R_t = \log P_t - \log P_{t-1} \dots\dots\dots(1)$$

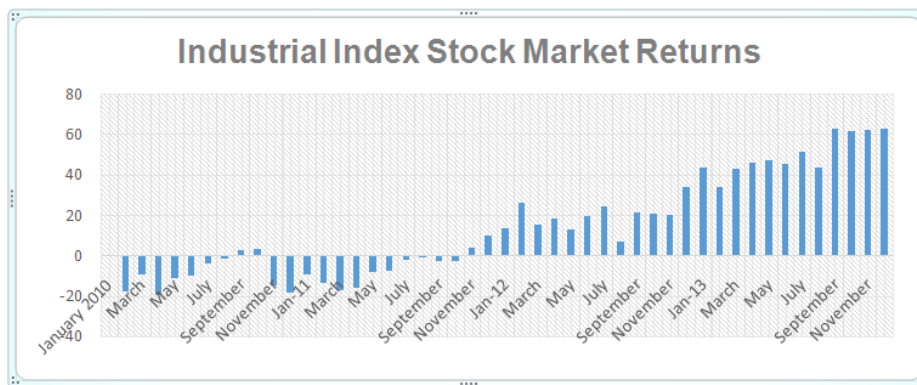
where;  $R_t$  is stock return.

$P$  is stock prices for year  $t$  and year  $t - 1$ .

3.6.1 Monthly Industrial Index Returns

Figure 4: Monthly Industrial Returns





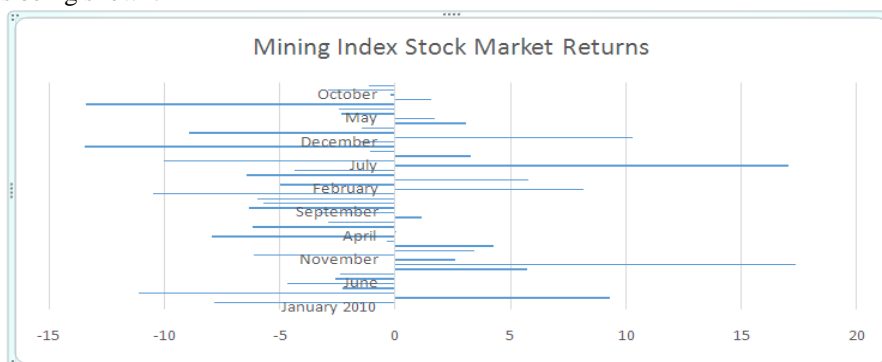
The two diagrams above clearly shows the Industrial Index, stock market returns. The period January 2010 to October 2012 has been characterized by negative returns implying it was not worth a period for investing in the market since losses have been realised. However, positive returns have been reaped for the last quarter Of 2012 to the year end of 2013, though at fluctuating levels. Investing in the stock market was worthwhile. This might be because of increasing investment confidence as the economy stabilizes and favourable policies in place.

### 3.6.2 Monthly Mining Index Returns

Figure 5: Monthly Mining Index Returns



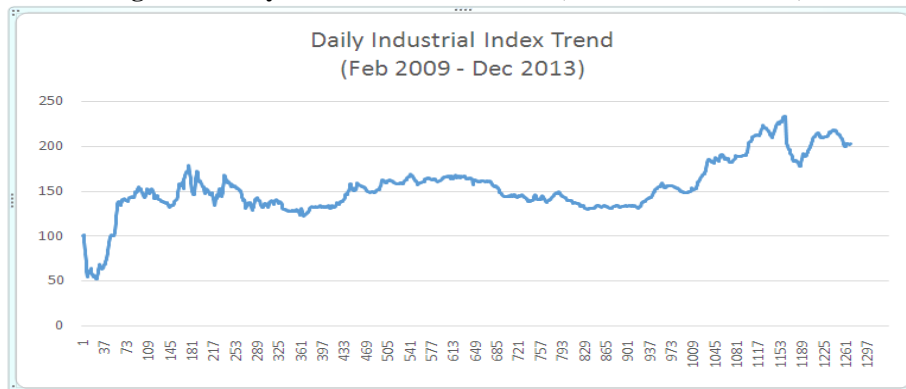
The Mining Index stock market returns trend are shown by the two graphs above. There is too much variability of the stock market returns. The stock returns are volatile with both negative and positive shocks. There is possibility of making profit by investing in such markets. However, there has been negative trend of returns being shown.



### 3.7 Daily Industrial Index Trend (Feb 2009 – Dec 2013)

The following graph shows the trend of the daily industrial index prices.

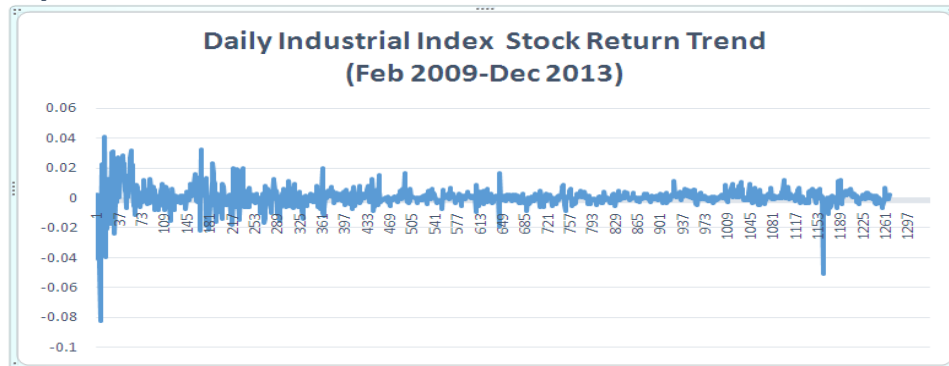
Figure 6: Daily Industrial Index Trend (Feb 2009 – Dec 2013)



From the graph above it shows a rising trend of the daily industrial stock prices over the entire period. However, there are some ups and downs on the way shown by fluctuations in the trend. The trend is almost the same as the one shown for monthly figures, making it clearly that the monthly performances are drawn from daily activities figures.

### 3.8 Daily Industrial Index Stock Returns

Figure 7: Daily Industrial Index Stock Returns



The graph above shows the volatility of stock market returns. As shown by the graph the returns are volatile as indicated by the fluctuations in the graph, with both negatives and positives. There volatility has been high during the beginning of the dollarisation period, and thereafter it has been constant in variation.

## IV. Econometric Analysis Of The Stock Market Returns

Financial markets react nervously to political disorders, economic crises, wars or natural disasters. In such stress periods prices of financial assets tend to fluctuate very much. Statistically speaking, it means that the conditional variance for the given past is not constant over time and the process is conditionally heteroskedastic. Econometricians usually say that volatility changes over time. Understanding the nature of such time dependence is very important for many macroeconomic and financial applications, e.g. irreversible investments, option pricing, asset pricing etc. Eviews econometric software have been used to provide the desired statistics for the stock markets and the results of the economic model used.

### 4.1 Portfolio Data

The table below shows the statistics for the mining and industrial stocks. The statistics gives us the nature of the market, the performance of the two markets and the likely risk they have.



**Table 1: Portfolio Data**

	MINING INDEX RETURNS	INDUSTRIAL INDEX RETURNS	INDUSTRIAL INDEX (DAILY)
MEAN	-1.406501	14.46980	0.000240
STANDARD DEVIATION	6.820190	25.40939	0.006810
SKEWNESS	0.722477	0.491259	-1.828702
KURTOSIS	3.701432	2.039230	31.17674
Jarque-Bera	5.052305	3.698155	42619.00
N	47	47	167

The Monthly industrial index has the highest mean return of 14.46, followed by the daily industrial index of 0.00024, and lastly the mining index with a negative mean of -1.4065. This shows that the Industrial stock market has performed better than the mining stock market for the period under study. This implies the stock markets returns are not identically distributed.

The industrial index return appears to be more volatile than the mining index return, as it registered a standard deviation of 25.4 while the mining index return has 6.82. It therefore implies that the mining stock market is more stable. However, daily stock returns have shown a lower variability in stock returns, with a standard deviation of 0.0068, implying stability in daily trading returns.

The Mining Index Returns and Daily Industrial Index Returns show evidence of fat tails, since their kurtosis exceeds 3, which is the normal value. The Daily Industrial Index Returns also shows evidence of negative skewness, which means that the left tail is particularly extreme.

Returns are thus not identically distributed with mean 0 and variance  $\sigma^2$  at each point in time. Instead, it is fair to say that  $\sigma_t^2$  changes with time t. This time-varying nature of variance is referred to in statistics as heteroscedasticity. The persistence of volatility (related to the time it takes for the effects of events in the stock market to dissipate) is an indication of autocorrelation in variances.

**4.2 Autocorrelations of Portfolio Returns**

MINING INDEX RETURNS					INDUSTRIAL INDEX RETURNS					INDUSTRIAL INDEX (DAILY)				
	AC	PAC	Q-Stat	Prob		AC	PAC	Q-Stat	Prob		AC	PAC	Q-Stat	Prob
1	-0.195	-0.195	1.9102	0.167	1	0.896	0.896	40.212	0.000	1	0.386	0.386	188.93	0.000
2	-0.063	-0.105	2.1131	0.348	2	0.828	0.126	75.293	0.000	2	0.262	0.134	276.49	0.000
3	0.137	0.108	3.0900	0.378	3	0.749	-0.066	104.63	0.000	3	0.173	0.041	314.71	0.000
4	-0.118	-0.078	3.8301	0.429	4	0.663	-0.088	128.20	0.000	4	0.020	-0.101	315.21	0.000
5	0.011	-0.010	3.8366	0.573	5	0.612	0.117	148.77	0.000	5	0.004	-0.008	315.23	0.000
6	0.015	-0.014	3.8489	0.697	6	0.559	0.011	166.33	0.000	6	-0.095	-0.100	326.69	0.000
7	-0.108	-0.092	4.5211	0.718	7	0.509	-0.026	181.28	0.000	7	0.010	0.105	326.82	0.000
8	-0.106	-0.165	5.1891	0.737	8	0.458	-0.052	193.65	0.000	8	0.093	0.118	337.90	0.000
9	0.000	-0.075	5.1891	0.818	9	0.415	0.031	204.09	0.000	9	0.048	-0.015	340.80	0.000
10	-0.032	-0.052	5.2537	0.874	10	0.357	-0.089	212.03	0.000	10	0.097	0.031	352.81	0.000
11	0.063	0.056	5.5114	0.904	11	0.297	-0.078	217.67	0.000	11	0.069	-0.004	358.96	0.000
12	-0.062	-0.070	5.7676	0.927	12	0.225	-0.116	221.00	0.000	12	0.108	0.071	373.94	0.000
13	-0.155	-0.199	7.3947	0.881	13	0.158	-0.026	222.68	0.000	13	0.084	0.023	382.98	0.000
14	0.054	-0.079	7.5975	0.909	14	0.115	0.073	223.61	0.000	14	0.091	0.069	393.59	0.000
15	-0.147	-0.220	9.1425	0.870	15	0.070	-0.026	223.96	0.000	15	0.138	0.071	418.21	0.000
16	-0.016	-0.142	9.1617	0.907	16	0.036	-0.027	224.06	0.000	16	0.084	-0.009	427.29	0.000
17	0.153	0.035	10.961	0.859	17	0.021	0.085	224.09	0.000	17	0.116	0.056	444.58	0.000
18	-0.004	0.055	10.962	0.896	18	-0.036	-0.198	224.20	0.000	18	0.003	-0.092	444.59	0.000
19	0.005	-0.008	10.964	0.925	19	-0.080	-0.053	224.73	0.000	19	-0.014	-0.016	444.86	0.000
20	0.071	-0.037	11.395	0.935	20	-0.117	0.026	225.90	0.000	20	-0.065	-0.073	450.37	0.000

The Industrial Index Returns shows substantial evidence of ARCH effects as judged by the autocorrelations of the squared residuals. The first order autocorrelation is 0.896, and they gradually decline to 0.021 after 17 lags. The same with the Daily Returns, where the first order correlations are 0.386 and are reduced to 0.003 after 18 lags. These autocorrelations are not large, but they are very significant. They are also all positive, which is uncommon in most economic time series and yet is an implication of the GARCH(1,1) model. Standard software allows a test of the hypothesis that there is no autocorrelation (and hence no ARCH). The test p-values shown in the last column are all zero to four places, resoundingly rejecting the “no ARCH” hypothesis.

According to the Q and LM Tests for ARCH Disturbances, the p-values of the Q and LM tests are all very small, less than .0001. Therefore, the errors in the regression model exhibit conditional heteroscedasticity. The Ljung-Box tests for the residuals have small p-values. These are due to small

autocorrelations that should not be of practical importance. The Mining Returns shows homoscedastic showing evidence of no ARCH effects.

**4.3 Garch Model Estimation**

According to Marius Matei (2009), GARCH is the most appropriate model to use when one has to evaluate the volatility of the returns of groups of stocks with large amounts (thousands) of observations. The appropriateness of the model is seen through a unidirectional perspective of the quality of volatility forecast provided by GARCH when compared to any other alternative model, without considering any cost component.

As against the ARCH model, the GARCH Model has only three parameters that allow for an infinite number of squared roots to influence the current conditional variance. This feature allows GARCH to be more parsimonious than ARCH model, which feature explains the wide preference for use in practice, as against ARCH. GARCH models require several years of daily data in order to be trustworthy. Furthermore, GARCH models are the only models that consider altering volatility and thus can cope with volatility clusters.

	<b>MINING INDEX RETURNS</b>	<b>INDUSTRIAL INDEX RETURNS</b>	<b>INDUSTRIAL INDEX (DAILY)</b>
<b>C</b>	5.953252 (0.0000)	21.68650 (0.1783)	3.22E-06 (0.0000)
<b>ARCH (1)</b>	-0.219690 (0.0002)	1.0318 (0.1723)	0.194732 (0.0000)
<b>GARCH (1)</b>	1.085843 (0.0000)	0.130870 (0.6415)	0.593167 (0.0000)
<b>CONVERGENCE</b>	28 Iterations	45 Iterations	3 Iterations
<b>ADJ R2</b>	-0.090883	-0.391858	-0.002824
<b>LOG LIKELIHOOD</b>	-151.5413	-203.6643	5017.856
<b>N</b>	47	47	1267

The regression results for GARCH (1,1) are presented above and for the Mining Returns and the Daily Industrial returns all p-values are small implying all GARCH parameters are significant to explain the stock market. In statistics GARCH (1)>> ARCH (1) implying reasonably long persistence of volatility.

For the Industrial returns, since p-value indicate insignificance at the rule of thumb 5% and even 10%, we could accept the null hypothesis implying that there is no strong evidence that there are higher returns during times of higher volatility.

A potentially more damaging issue is the frequency of data used. It is conceivable that volatility estimated from daily data is more precise than GARCH volatility estimated from monthly data simply because of the higher frequency of daily data.

**4.4 Variance Equation**

Dependent Variable: RETURNS				
Method: ML - ARCH				
Date: 01/25/14 Time: 11:29				
Sample(adjusted): 2 1268				
Included observations: 1267 after adjusting endpoints				
Convergence achieved after 87 iterations				
	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	2.691832	3.212639	0.837888	0.4021
Variance Equation				
C	2.62E-06	1.22E-07	21.58377	0.0000
ARCH(1)	0.459706	0.019935	23.05967	0.0000
GARCH(1)	0.562894	0.014312	39.33126	0.0000
R-squared	-0.028039	Mean dependent var		0.000240
Adjusted R-squared	-0.030481	S.D. dependent var		0.006810
S.E. of regression	0.006913	Akaike info criterion		-7.941627
Sum squared resid	0.060359	Schwarz criterion		-7.925386
Log likelihood	5035.021	Durbin-Watson stat		1.187950
OVER FLOW				

Dependent Variable: MININRETURNS				
Method: ML - ARCH				
Date: 01/25/14 Time: 12:20				
Sample(adjusted): 2 48				
Included observations: 47 after adjusting endpoints				
Convergence achieved after 47 iterations				
	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	-0.014188	0.026102	-0.543555	0.5867
Variance Equation				
C	4.384870	0.754294	5.813214	0.0000
ARCH(1)	-0.180632	0.037122	-4.865904	0.0000
GARCH(1)	1.108221	0.071125	15.58124	0.0000
R-squared	-0.029586	Mean dependent var		-1.406501
Adjusted R-squared	-0.101418	S.D. dependent var		6.820190
S.E. of regression	7.157683	Akaike info criterion		6.615842
Sum squared resid	2202.994	Schwarz criterion		6.773301
Log likelihood	-151.4723	Durbin-Watson stat		2.323155

The Daily Industrial returns regression equation presents the three coefficients in the variance equation listed as C, the intercept; ARCH(1), the first lag of the squared return; and GARCH(1), the first lag of the conditional variance. The coefficients sum up to a number less than one, which is required to have a mean reverting variance process. Since the sum is very close to one, this process only mean reverts slowly. Standard errors, Z-statistics (which are the ratio of coefficients and standard errors) and p-values complete the table and are all significant.

For the Mining Returns, the sum of C, ARCH (1) and GARCH (1) adds to a number greater than 1, implying that it has no mean reverting variance. However the coefficients are significant at 1% level. Both the regressions converge implying correctly specified. The Monthly industrial stock returns regression failed to converge and hence there was an overflow, implying a GARCH model inappropriate.

### V. Concluding Remarks

The three main purposes of forecasting volatility are for risk management, for asset allocation, and for taking bets on future volatility. A large part of risk management is measuring the potential future losses of a portfolio of assets, and in order to measure these potential losses, estimates must be made of future volatilities and correlations.

Models of conditional heteroskedasticity for time series have a very important role in today's financial risk management and its attempts to make financial decisions on the basis of the observed price asset data in discrete time. Prices are believed to be non-stationary so they are usually transformed in the so-called log returns. Log returns are supposed to be stationary, at least in periods of time that are not too long.

The Zimbabwean Industrial Stock market has proved that there is a strong relationship between volatility and market performance. Volatility tends to decline as the stock market rises and increase as the stock market falls. When volatility increases, risk increases and returns decrease. Risk is represented by the dispersion of returns around the mean. The greater the dispersion of returns around the mean, the larger the drop in the compound return. Region and country economic factors, such as tax and interest rate policy, contribute to the directional change of the market and thus volatility.

The Mining Stock market has shown somewhat behaviour in terms of volatility, this might be due to the nature of data used (monthly data). It has shown to be less volatile as given by the GARCH Model regression and the presence of ARCH effects. This implies that investment in the market should be encouraged as it seems to be decreasing in performance over time. In reality the sector comprises of very few mining companies, and during the last decade many mining companies have been facing difficulties in operations. However, after the introduction (adoption) of the stable currencies, the sector remained undercapitalized as shown by return trends presented earlier.

The higher level of volatility that comes with bear markets has a direct impact on portfolios. It also adds to the level of concern and worry on the part of investors as they watch the value of their portfolios move more violently and decrease in value. This causes irrational responses which can increase investors' losses. As an investor's portfolio of stocks declines, it will likely cause them to "rebalance" the weighting between stocks and bonds by buying more stocks as the price falls. Investors can use volatility to help them buy lower than they might have otherwise.

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