Examination of South African Market Neutral Hedge Funds

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Abstract

South Africa has recently passed new regulations governing its hedge fund industry. This regulation has the potential to dramatically increase the appeal of the industry as a whole, and thus its growth. In order to reduce the risks associated with these changes, an analysis of the risk structure of the industry is required. This study focuses on South African ‘market neutral’ hedge funds, which claim to achieve returns that are “neutral” to the general equity market. The study tests these claims using a variety of tests of neutrality, and then goes on to examine the degree of systemic risk building up within these funds. Our results suggest that a large proportion of ‘market neutral’ funds fails a test of neutrality, and that these funds are subject to moderate network effects and systemic risk.

Keywords: Hedge Fund, Systemic Risk, Neutrality, Liquidity.

1. Introduction

The first hedge funds were started with the aim of constructing portfolios of related securities that required a zero net investment, by taking offsetting positions in these securities with the objective of profiting from apparent pricing anomalies and hence making arbitrage profits (Patton 2009). This had some degree of appeal because by taking such offsetting positions, these "new" investment vehicles (hedge funds) were essentially offering diversification benefits, by reducing the portfolio's sensitivity to movements in the market return.

Over the years, many different "styles" of hedge funds have emerged. A hedge fund's "style" is a categorization of the type of investment strategies mainly implemented by the hedge fund. These include, among others, event-driven hedge funds, fund-of-funds hedge funds, market neutral hedge funds, equity-hedge hedge funds, equity non-hedge hedge funds, etc. (HedgeFundResearch 2016).

In recent years, the term "hedge funds" has been used a lot in the media and thus now forms part of the collective consciousness. This is in part because hedge funds have grown as an investment allocation in institutional portfolios (Rittereiser and Kochard 2010), and as a consequence they have had a greater impact on the market. Furthermore, hedge funds have experienced consistently superior market returns over the past couple of decades, by combining a variety of complex trading strategies and philosophies. This outperformance of the market, in addition to its exclusivity and private nature, has spurred much interest in the industry.

However, there has been some degree of negative publicity and mythicizing of the hedge fund industry - especially after the market crash of 2008 - which has led to a significant flock of academic work on the industry.

Nevertheless, in South Africa there have been recent regulatory changes relating to hedge funds. For this reason, it would be of interest to examine hedge fund characteristics, in order to better understand these investment vehicles and the benefits they offer investors. These regulatory changes impose additional governance and reporting requirements for hedge funds in South Africa, and introduces a new category of hedge funds with the intention of making hedge funds more accessible to the retail investor. The implications of this regulation on hedge fund governance are likely to improve the industry's overall credibility and thus increase investor confidence in hedge funds (McClelland, 2015). A particular type of institutional investor - pension funds - that oversees about 2.5 trillion Rands (McClelland, 2015), could unlock over 10% of their funds to invest in the hedge fund industry as a result of this new regulation, leading to significant growth in the hedge fund industry (McClelland, 2015).

This paper will examine "Market Neutral" Hedge Funds in the South African context by focusing on answering the following questions: 1) Are market neutral funds truly market neutral? 2) What is the degree of autocorrelation within the return streams of such market neutral funds? 3) Are risks being understated by market neutral profiles and is there systemic risk building up within these funds?

Capocci (2006) defines market neutral funds as "funds that take long and short positions in various securities while trying to avoid exposure to the equity market". Their objective is to achieve a positive Jensen's Alpha[1], independent of the market risk-return structure Capocci (2006). Furthermore, the market neutral categorization of hedge funds is of particular interest since it represents about 28.3% of individual funds in the global CISDM (Center for International Securities and Derivatives Market) database Capocci (2006).

2. Data

The data set used in this study consists of:

[1] "Jensen's alpha is used to determine the excess return of a stock, other security, or portfolio over the security's required rate of return as determined by the Capital Asset Pricing Model. This model is used to adjust for the level of beta risk, so that riskier securities are expected to have higher returns" HedgeFundResearch. (2016). https://www.hedgefundresearch.com/family-indices/hfri .

- Individual monthly returns, net of all fees, achieved by forty different self-described “market neutral” funds in the South African hedge fund industry. The database includes both “live” and “dead” hedge funds – a dead fund is one that stops reporting its results into the database, while a live fund is one that is still reporting its results into the database. This data was sourced by my supervisor, and affords anonymity for each of the funds; thus, in the following analysis, each fund is indexed and referred to by its index in the data frame, e.g. “Fund 1” or “Return 1”.
- The JSE All Share Index (ALSI), used as a proxy for the market portfolio. This data was sourced from the Bloomberg database, using a Bloomberg Terminal.
- The JSE Africa Banks Index (JBNKS), the JSE Africa Insurance Index (JINSR) and the JSE Africa Financial 15 Index (FINI15). This data was sourced from the Bloomberg database, using a Bloomberg Terminal.

Some of the challenges faced during the analysis phase included 1) sorting out the data according to date in a consistent manner, since the fund return observations were for varying time periods; 2) accounting for the short histories in some hedge funds when doing the analysis; and 3) the lack of Assets Under Management data for each fund Furthermore, the South African market neutral hedge fund industry is relatively (compared to Europe, Asia or US) small, and thus the number of hedge funds reporting their returns to our database is also relatively small. This limits the power of the results obtained from this study.

Summary statistics for the hedge funds and the market return are presented in Table 1. To obtain these figures, a hedge fund index was constructed as an equally-weighted average of hedge fund returns, starting when the database first contained ten funds (November 2005), and ending in February 2016. A minimum of ten funds is imposed for the creation of such an index to reduce the degree of bias and influence in the index. A graph showing the number of hedge funds contributing data to the database can be found in the appendix (figure 1).

These figures suggest that, on average, market neutral funds achieve lower, but more stable returns compared to the market. This is evidenced by the lower standard deviation, absolute skewness and kurtosis experienced by the market neutral hedge funds. The lower standard deviation implies that market neutral hedge funds are less risky than the market portfolio; the skewness and kurtosis are measures of the distributional features of the data – high values of these higher moments indicate greater risk to extreme events.

Table 1: Summary statistics of Hedge Fund and ALSI returns, for the period starting in November 2005 and ending in February 2016

		Hedge Fund Index	ALSI
1	Return	0.85%	0.99%
2	standard Deviation	0.75%	4.45%
3	Skewness	0.12	-0.27
4	Kurtosis	0.37	0.86
5	Minimum	-1.26%	-13.96%
6	Maximum	2.80%	12.29%
7	Autocorrel, lag1	0.23	-0.07
8	Autocorrel, lag2	0.22	0.12

For each row in this table, the value reported represents the cross-sectional mean value of the statistic. "Market Neutral" represents the database of market neutral hedge funds; "ALSI" represents the JSE All Share Index returns.

Another important statistical feature of hedge funds is measured using the Sharpe Ratio. This is a measure of the fund's risk-adjusted return, and gives a summary statistic of the risk-return characteristics of the fund. The above table suggests that the hedge funds in our database achieve a 1.13% return for each unit of risk taken; while the market only achieved a 0.22% return for each unit of risk taken. A graph showing the relationship between a fund's return and its standard deviation can be found in the appendix (figure 2). From this graph, it is evident that the general trend is that the greater a fund's standard deviation of returns, the greater its monthly returns. This is in accordance with the idea that in order to achieve higher returns, it is necessary to take on greater risk.

3. Examining Market Neutrality

3.1 Correlation (or Beta) Neutrality

"A fund may be said to be market neutral if it generates returns that are uncorrelated with the returns on some market index, or a collection of market risk factors" (Patton 2009). Testing for correlation neutrality can be done empirically via standard linear correlation, as in the study by Patton (2009). Alternatively, tests for correlation neutrality can be based on classical models of asset returns such as the CAPM, as in the study by Capocci (2006), and testing for a significant market coefficient through a linear regression model.

This study follows an approach similar to Patton (2009). The average correlation between the market neutral hedge funds and the market was 0.192, and the 5th and 95th sample quantiles of the cross-sectional distribution of correlation coefficients was [- 0.05, 0.61], indicating that substantial cross-sectional correlation exists between the funds and the market return. A histogram of the hedge fund correlations with the market can be found in the appendix (figure 3).

Using the approach of Politis and Romano (1994), a stationary bootstrap algorithm is run with optimal block length determined by the method of Politis and White (2004). Following this approach, 35% of the funds in the database exhibit significant correlation with the ALSI at the 5% level of significance. This statistic is very high, and therefore challenges the neutrality of the hedge funds in our database.

A consideration of correlation neutrality as a measure of market exposure is sufficient for investors who exhibit quadratic utility functions or face normally distributed returns (Patton 2009), and thus for whom the mean-variance framework is appropriate. However, Fung and Hsieh (1999) provide evidence that decision making based on this framework would be inaccurate because it does not take into account the probability of large negative returns (left tail risk). We then consider alternative measures of neutrality as well.

3.2 Mean Neutrality

A fund is said to be mean neutral if its expected return is independent of the market return (Patton 2009). Formally:

$$E[r_{it} \mid r_{mt}] = E[r_{it}] \forall r_{mt}$$

Where r_{it} is the return on fund i in month t; and r_{mt} is the return on the market in month t.

This definition requires the absence of either a linear nor nonlinear relationship between the fund return and the market return; it does not take into account the fact that investors may desire or dislike certain relations between the expected fund return and market return (Patton 2009).

To test for mean neutrality, a variety of methods could be employed. For example, Agarwal and Naik (2004) employ piecewise linear regression. A nonparametric regression approach could also be used (Patton 2009). Patton (2009) employs a Taylor series approximation to the conditional mean function, $\mu_i(r_{mt}) = E[r_{it} \mid r_{mt}]$:

$$r_{it} = \beta_0 + \beta_1 r_{mt} + \beta_2 r_{mt}^2 + \ldots\ldots + e_{it}\,,$$

and then tested for non-zero beta via a standard Wald test. Note that the nonlinear relationship between the market returns and fund returns is accounted for in this analysis by considering the above Taylor polynomial transformation of the conditional mean function.

Using this approach, 40% of funds in the database exhibited significant mean non-neutrality. This indicates that the market fund Granger causes a significant portion of 40% of market neutral hedge fund returns. This figure is also very high, and challenges the neutrality of the hedge funds in our database.

3.3 Variance Neutrality

This is a risk-based measure of neutrality which represents the fund's risk by its variance. It is defined:

$$V[r_{it} - \mu_i(r_{mt}) \mid r_{mt}] = V[r_{it} - \mu_i(r_{mt})] \qquad \text{(Patton 2009)}$$

To test for variance neutrality, Patton (2009) approximate the true variance function by a Taylor series polynomial:

$$\begin{aligned} &\sigma_i^2(r_{mt}, e_{it-1}) = \alpha_0 + \alpha_1 r_{mt} + \alpha_2 r_{mt}^2 \\ &r_{it} = \mu_i(r_{mt}) + e_{it} \end{aligned}$$

and uses a Wald test in a similar fashion to the previous section. Similarly, here the nonlinear relationship between the market returns and fund returns is accounted for in this analysis by considering a Taylor polynomial transformation of the conditional mean and conditional variance functions.

Using the method described above, 22.5% of funds in the database exhibited significant variance non-neutrality at the 5% significance level. This indicates that a significant proportion of these funds' risk profile is influenced by the market return; this suggests a potentially dangerous level of systemic risk within these funds, and further justifies the analysis in section 4. This is especially dangerous if hedge fund managers do not disclose this risk to investors, or if they do not account for it in their trading activities (ignoring volatility can lead to volatility risks, which manifests itself during periods of economic downturn (Fornari and Mele 2013)). This could lead to investors seeing significant losses in value overnight, further leading them to disinvest from their funds and causing a liquidity trap in the market.

3.4 Value-at-Risk (quantile) Neutrality

A VaR-neutral portfolio is one with a VaR that is unaffected by the market portfolio return" (Patton 2009). We consider conditional VaR neutrality, however, since unconditional VaR-neutrality is subject to limitations imposed by the non-occurrence of mean or variance neutrality (Patton 2009). Conditional VaR neutrality is defined:

$$VaR\left(\frac{r_{it}-\mu_i(r_{mt})}{\sigma_i(r_{mt})} \mid r_{mt}\right) = VaR\left(\frac{r_{it}-\mu_i(r_{mt})}{\sigma_i(r_{mt})}\right),$$

where $\frac{r_{it}-\mu_i(r_{mt})}{\sigma_i(r_{mt})}$ is the standardized fund return, εi_t ; $\mu_i(r_{mt})$ is the conditional fund mean return function and $\sigma_i(r_{mt})$ is the conditional fund return variance function, as in the previous parts.

Patton (2009) employs a test of Christoffersen (1998) to examine whether the probability of a fund exceeding its VaR is affected by another fund exceeding or not exceeding its VaR.

This study firstly considers every period where the market standardized return was less than its Value-at-Risk at that period; for each hedge fund, it then considers two distinct time series of hedge fund returns: the fund return time series conditional on the market's standardized return being less than its Value-at-Risk at that period (the conditioned sample); and the unconditioned fund return time series. A test of Kupiec (1995) on the two samples is then implemented, and the null hypothesis of VaR-neutrality is rejected for a fund if the conditional probability of the fund time series exceeding its VaR is less than the corresponding unconditional probability.

Using the above method, none of the funds exhibit significant VaR non-neutrality. Although there is a robust data requirement for this test, which may introduce some bias, these results should not be surprising; table 1 presented evidence that market neutral hedge funds in our database exhibited low kurtosis, skewness and standard deviation in comparison to the market. This implies a more stable distribution of returns, with a lower frequency of peaks and thus a lower probability of experiencing returns that are more extreme than that period Value-at-Risk.

3.5 Tail Risk and Tail Neutrality

The concept of tail neutrality relates to neutrality during extreme events (i.e. at the tails of the fund and market distributions). A fund is tail neutral if the probability that it achieves extreme returns is unaffected by the market return; an extreme event in the market should therefore have no effect on a fund that is tail neutral (Patton 2009).

In order to determine a fund's tail neutrality, it is first necessary to evaluate the fund's exposure to tail risk. To do this, the extreme dependence between the fund's return and the market return must first be measured. Agarwal, Ruenzi and Weigert (2016) define a fund's tail sensitivity (TailSens) via the lower tail dependence of its return r_{it} and the market return r_{mt} using

$$TailSens = \lim_{q \to 0} P\left(r_{it} \le F_i^{-1}(q) \middle| r_{mt} \le F_m^{-1}(q)\right),$$

where F_i (F_m) denotes the marginal distribution function of the returns of hedge fund i, r_{it} (the market return r_{mt}) in a given period; and $q \in (0,1)$ is the argument of the distribution function. Intuitively, a fund with high tail sensitivity is more sensitive to market crashes. The above measure of tail sensitivity considers the distribution of returns in the lower q quantile, but does not give any indication of how bad the returns in this lower quantile actually are. In order to account for this, and obtain a more informative measure of tail risk, Agarwal, Ruenzi and Weigert (2016) define a fund's tail risk (TailRisk) as

$$TailRisk = TailSens \cdot \frac{|ES_{r_{it}}|}{|ES_{r_{mt}}|}$$

where $ES_{r_{it}}$ and $ES_{r_{mt}}$ denote the expected shortfall (or conditional VaR) of the hedge fund return and the market return, respectively. Taking the ratio of a fund's ES with respect to the ES of the market allows one to measure the fund's tail risk relative to the market.

Following the methodology of Agarwal, Ruenzi and Weigert (2016), TailRisk for hedge fund *i* in month *t* is computed based on a rolling window of 24 monthly returns. This is done non-parametrically, and purely based on the empirical return distributions of the hedge funds and the market. We take q = 0.05 for our estimation of TailSens, and also compute the 5% Expected Shortfalls in TailRisk.

Furthemore, TailSens for hedge fund *i* is computed discretely, by firstly determining the months/periods during which the market experienced its lower 5% returns for a specific 24-month window. Then we also determine the months/periods during which hedge fund *i* experienced its lower 5% returns for the same 24-month window. We then count the number of occurrences where the hedge fund's lower 5% returns over the 24-month window considered occurred in the same month as the market's lower 5% returns over the same 24-month window. TailSens is then obtained by dividing this count by the number of months that saw the market achieve its lower 5% return.

For example, suppose the window runs from January 2007 to December 2008. Further suppose that the market's lower 5% returns over this window occurred in February 2008 and September 2008. If none, one, or both of fund *i*'s worst return realizations occur in February and/or September 2008, then TailSens is computed as 0, 0.5, or 1, respectively. The fund's tail risk is then computed by multiplying TailSens by the ratio of $ES_{r_{it}}$ and $ES_{r_{mt}}$.

A fund is therefore said to be tail neutral, at the 5% significance level, if its tail risk is less than 5%.

It is important to note that, given that we are using a 24-month period, the data requirement imposed by the tail risk neutrality analysis is that each hedge fund must have a minimum of 24 return observations. This limits our database to 32 funds.

Using the above methodologies, the average tail risk for the funds in the database is 5.77%. This statistic is very low, and is in accordance with the literature on hedge fund tail risk suggesting that market neutral hedge funds predominantly exhibit low tail risk. Agarwal, Ruenzi and Weigert (2016) show that tail risk have significant predictive power over fund returns, and can be used to explain the cross-sectional variation in hedge fund performance. In this sense, it can be used as a credible measure of risk for the purpose of risk-adjusted performance evaluation.

Figure 4 shows the relationship between the tail risk and average monthly returns of hedge funds in our database. From the above figure, it is evident that hedge funds with the lowest tail risk tend to achieve the greatest return. As a fund's exposure to tail risk increases, its return decreases. Furthermore, the return spread between funds with lower tail risk and those with higher tail risk is approximately 0.35% per month. This implies that market neutral funds with the lowest tail risk achieved annual returns that are approximately 4.15% higher than market neutral funds with the highest tail risk. This is in contrast to other literature (Agarwal, Ruenzi and Weigert 2016) where funds (average across all styles) with highest tail risk achieved annual returns 4.8% higher than those with the lowest tail Risk. This is an indication of the fundamental difference in the risk-return characteristics of market neutral hedge funds compared to other types of hedge funds; market neutral hedge funds aim to achieve returns that are not sensitive to market returns (including market crashes) and hence, it makes sense that those market neutral hedge funds that satisfy this mandate/objective are more profitable than those that do not.

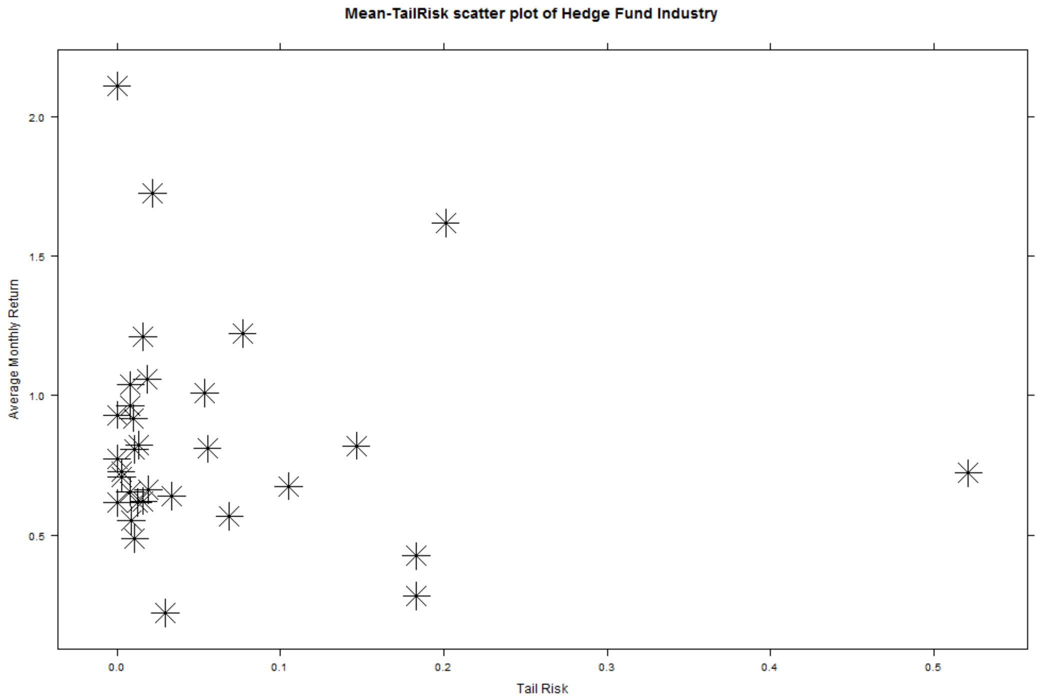

Figure 4: Relationship between hedge fund tail risk and average monthly returns

Finally, 31.25% of the funds in our database experienced tail risk significantly (at the 5% level) different from zero, and thus fail the test of tail neutrality. Although this figure is high, when compared to other hedge fund styles, it is acceptable, given that we are considering market neutral hedge funds.

4. Examination of Systemic Risk

4.1 Illiquidity and Correlation

As suggested by Chan, Getmansky, Haas and Lo (2005), a fund's degree of autocorrelation is considered as a proxy for the amount of liquidity risk that it is exposed to. This is because managers of portfolios with illiquid securities (such as hedge fund portfolios) typically have discretion in marking the portfolio's value (Getmansky, Lo and Makarov 2004). Given such discretion, managers have the incentive to smooth their returns in each period; this smoothing mechanism results in serial correlation in fund returns.

Table 2 in the Appendix presents the values of the autocorrelation function up to lag 6, for each of the funds in the database. An inspection of this table shows that the first, second and fourth-order autocorrelations are significant. This first two lags being significant reflects the tendency of fund returns being slow to react to new information, while the significance of the fourth lag may provide evidence of such smoothing behaviour.

Table 3 in the Appendix presents the values of the average mutual information up to lag 6, for each of the funds in the database. The mutual information between two variables X and Y is the uncertainty that is common to both X and Y. It is a measure of the dependence between X and Y, which provides a more general measure of dependency than a traditional correlation analysis (which is only a measure of linear dependence). An inspection of this table reveals a more risky profile, with the information at all 6 lags considered significantly influencing the returns.

However, this cross-sectional analysis may produce misleading results. In order to obtain a more robust test of serial correlation, this study applies the Durbin-Watson test of no autocorrelation from Durbin and Watson (1971) to each individual fund; 27.5% of funds failed the test at the 5% level of significance, and 37.5% of funds failed the test at the 10% level of significance. These suggest that the market neutral hedge fund industry as a whole is prone to moderate levels of systemic risk.

4.2 Granger Causality

Billio, Getmansky, Lo and Pelizzon (2010) suggest Granger causality as a measure of co-integration and connectedness between financial institutions. X is said to "Granger-cause" Y if past values of X contain information that helps predict Y above and beyond the information contained in past values of Y alone (Billio *et al.* 2010). The concept of Granger causality was mentioned in section 3.2, when considering the concept of mean neutrality. In that case, Granger causality between the market index and the hedge fund was tested; we now consider Granger causality between one fund and another, to determine the overall degree of interconnectedness in our database of funds.

4.2.1 Granger Causality within the Hedge Fund Industry

For an economically significant analysis of Granger causality, it is required for all the funds to have an equal number of observations over the period of interest, since otherwise some funds may lose their forecasting power over other funds; we thus consider a sub-period analysis of all the funds in our database that reported uninterrupted returns in the three and a half year period from July of 2006 to December of 2009. This period was chosen for its financial significance – it is the period leading into the crash of the financial market in 2008/09, including a few months following this event. An analysis of Granger causality over this period would consequently be of interest to the reader.

Of the funds in our database, 15 reported uninterrupted returns over the period of investigation. For each fund, we conduct Granger (1988)'s test for linear Granger causality with the other funds, and construct a 15x15 data frame of p-values of this test. The results obtained are presented in the following table:

Table 4: Granger Causality Test p-values across all funds in the sub-period analysis

	R0	R3	R6	R7	R10	R11	R12	R13	R16	R18	R24	R26	R27	R29	R38
R0		0.41	0.32	0.98	0.57	0.68	0.96	0.66	0.16	0.66	0.42	0.63	0.23	0.57	0.58
R3	0.59		0.32	0.28	0.89	0.29	0.2	0.41	0.07	1	0.34	0.33	0.85	0.08	0.64
R6	0.24	0.35		0.73	0.16	0.79	0.85	0.29	0.49	0.3	0.72	0.78	0.94	0.45	0.89
R7	0.24	0.01	0.84		0.21	0.5	0.64	0.55	0.04	0.54	0.47	0.18	0.57	0.73	0.47
R10	0.92	0.03	0.11	0.76		0.2	0.07	0.39	0.46	0.49	0.06	0.74	0.32	0.04	0.13
R11	0.03	0.96	0.97	0.08	0.38		0.24	0.79	0.63	0.29	0.01	0.02	0.67	0.57	0.36
R12	0.14	0.69	0.43	0.31	0.45	0.94		0.78	0.91	0.3	0.54	0.98	0.24	0	0.96
R13	0.66	0.95	0.9	0.48	0.62	0.08	0.82		0.83	0.36	0.44	0.68	0.8	0.28	0.52
R16	0.03	0.88	0.39	0.59	0.23	0.21	0.53	0.99		0.79	0.09	0.55	0.71	0.31	0.58
R18	0.79	0.81	0.76	0.14	0.97	0.9	0.91	0.23	0.87		0.87	0.25	0.11	0.88	0.15
R24	0	0.81	0.48	0.15	0.49	0.67	0.54	0.79	0.99	0.69		0.8	0.68	0.32	0.52
R26	0.53	0.74	0.95	0.34	0.36	0.66	0.05	0.95	0.01	0.69	0.36		0.67	0.01	0.9
R27	0.79	0.59	1	0.56	0.31	0.82	0.94	0.5	0.38	0.08	0.97	0.57		0.58	0.21
R29	0.03	0.78	0.38	0.13	0	0.38	0.89	0.22	0.66	0.01	0.73	0.73	0.82		0.16
R38	0.44	0.76	0.72	0.76	0.93	0.67	0.75	0.79	0.75	0.74	0.74	0.68	0.7	0.86	

Table 4 reports the p-values of the test of Granger Causality across all the funds that reported uninterrupted returns in the period from July 2006 to December 2009, where “Return” has been abbreviated to “R” for ease of tabulation. To obtain these values, for each cell, we test whether the variable in the corresponding row Granger causes the variable in the column, for each of the 15 columns and rows. The highlighted cells reflect the combination of funds for which there was a significant (at the 10% level, instead of 5%, to account partly for the shortfalls of such a linear test) causality factor. For example, one can see that funds eleven, sixteen, twenty-four and twenty-nine all Granger-cause fund zero’s returns.

These result imply moderate interconnectedness in this basket of funds since the number of non-diagonal cells that are highlighted is moderate. Such interconnectedness may be as a result of various things, e.g. managers could be making use of similar trading strategies and therefore invest in similar assets; or the managers may trade through the same broker, etc. The implications of such interconnectedness for investors is that invested funds are likely to flow rapidly between the hedge funds as managers try to outperform each other; this may lead to greater volatility in asset values, and uncertainty for investors.

4.2.2 Granger Causality between Hedge Funds, Banks and Insurance Companies

Various studies have shown that the hedge fund industry is significantly affected by the banking industry and the insurance industry, for example Billio et al. (2010). This is because the financial system today is interdependent, and the different trading activities executed by these various institutions are linked. This leads to a greater degree of systemic risk in the entire financial system. For this reason, when considering the topic of systemic risk in one of these institutions, it is important to also consider how the other institutions affect the institution of investigation.

The following table presents the Granger Causality test p-values between a Hedge Fund index (created as an equally weighted average of fund returns over the period of investigation), the JSE Africa Bank Index (JBNKS), and the JSE Africa Insurance Index (JINSR). The study was carried out for two non-overlapping periods: from July 2006 to December 2009; and from July 2012 to December 2015. This was done in order to analyse the change in the relationship over time between the different industries.

Table 5: Granger Causality Test p-values between Hedge Fund Index, Bank Index, and Insurance Index.

2006 to 2009

	HFIndex	Banks	Insurance
HFIndex	0	0.95	0.16
Banks	0.93	0	0.06
Insurance	0.17	0.05	0

2012 to 2015

	HFIndex	Banks	Insurance
HFIndex	0	0.5	0.02
Banks	0.75	0	0.08
Insurance	0.03	0.56	0

In a manner similar to table 4, in order to obtain the values in each cell, we test whether the variable in the corresponding row Granger causes the variable in the column, and highlight the cells where there is a significant causality factor (at the 10% significance level).

The above table shows that, at the 10% significance level, there are significant causal relationships between banks and insurance companies (in both directions) during the period from 2006 to 2009. In this period, the hedge fund industry had no causal relationship with the other two industries. However, during the period from 2012 to 2015, the hedge fund industry had a significant causal relationship with the insurance industry (in both directions); furthermore, during this period, banks also granger caused the insurance industry, but were not granger caused by that industry.

This observation may seem contradictory on the surface, considering that the period from 2006 to 2009 included a market crash, but saw no causal relationship involving the hedge fund industry. However, this should not be surprising, since our database of hedge funds contains only market neutral hedge funds, whose objective is to achieve returns that are neutral to the market. This analysis is indicative of the success of the market neutral hedge fund industry in general to perform independently during periods of market distress. The fact that the market neutral hedge fund industry exhibited causal relationships during the period 2012 to 2015 but not during 2006 to 2009 also indicates managerial skill, and their ability to time market crashes. This allows the managers to profit from booming or expansionary market conditions, but protect themselves from crashing or recessionary market conditions. This ability therefore limits the industry's exposure to systemic risk.

4.3 Regime-switching Models

Billio *et al.* (2010) also propose a model driven by the sudden shifts in the expected returns and volatilities of financial returns – the regime-switching model of expected returns. In this model, only two states exist; the low regime and a high regime. The choice of the actual model has been specified differently by different authors, and for different financial institutions. Hamilton (1990) proposes to model the regime-switching behaviour according to the business cycle, while Billio *et al.* (2010) use a simple two-chain Markov regime-switching model.

A simple version of a Self-Extracting Threshold Autoregressive model (SETAR) - such as those considered by Tong (1990) – is employed in this study, with no forecasting step, and a threshold variable (call it Z) constructed as a weighted linear combination of the fund returns at lags one, two and three; weights of 0.8, 0.15, and 0.05 respectively are assigned to these lagged variables. Using this model, a fund is considered to be in the low regime if Z is less than a rolling threshold value (say W) that is determined by continuous regression of the time series up till the current time; evidently, a fund that is not in the low regime is in the high regime. From this model specification, a fund being in the low regime state would be undesirable, while being in the high regime state would be desirable.

The analysis is mostly graphical. It starts with a comparison of summary statistics (such as the mean, standard deviation, kurtosis, etc.) from both the low-regime and high-regime time series. Then, a plot of the rolling probability of being in the low regime is generated, beginning in the third year of life of fund 20 (this is done in order to satisfy the data-intensive requirements of SETAR models). The evolution of this plot indicates the change in the level of systemic risk that a fund is susceptible to over time. Additionally, a cross-fund analysis of the probability of being in a low regime provides a robust indication of the degree of commonality across the hedge funds, which is a proxy for systemic risk.

5. Case Study: Fund ID 209's Systemic Risk

We now focus our attention on the fund with ID 209 in the database. This fund has the largest number of observations, and one of the best mean return in the database. Furthermore, it is still part of the live fund database, and thus is of greater relevance to the reader. This section provides a case study of this fund.

The following table represents summary statistics for the fund:

Table 6: Summary statistics of fund 209

Statistic	**Value**
Min	-2.12%
Max	13.00%
Mean	1.73%
Standard Deviation	2.09%
Kurtosis	8.14
Skewness	2.28
Semi-deviation	1.07%
Cornish-Fisher 95% Expected Shortfall	- 6.33%

Annualized alpha (relative to ALSI)	21.53%
Active Premium (relative to ALSI)	9.88%

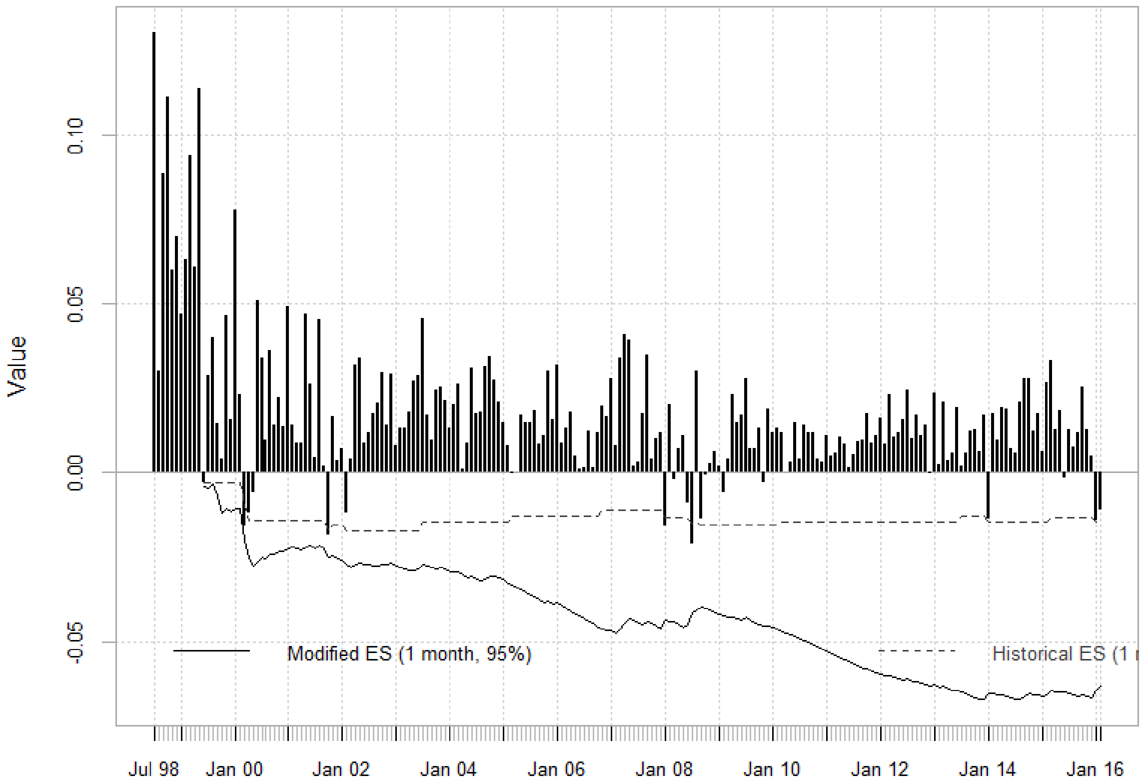

Figure 6: A graph showing the monthly returns of fund 209 (the bar graph) along with the 95% Cornish-Fisher (solid line) and Historical (dotted line) Expected shortfall.

From the above table and graph, it is evident that fund 209 has been achieving superior returns (with an annualized alpha over 21% and active premium of 9.88% relative to the ALSI benchmark). However, the fund's high kurtosis may be indicative of its vulnerability to higher moments of the expected return distribution.

5.1 Neutrality

Using the methods outlined in section three, fund 209 fails every test of neutrality except for Value-at-Risk neutrality, which no fund fails, at the 5% level of significance. These results suggest that fund 209 is highly influenced by the market, and question the fund's self-classification as "market neutral"

5.2 Systemic Risk

Table 4 in section 4 analyses the Granger Neutrality for all funds. In this table, "R29" refers to fund 209. This table shows that fund 209 is significantly interconnected with 8 different funds. That is, fund 209 either Granger-causes or is Granger-caused by 8 different funds. This is a highly significant statistic; 20% of all the funds in the database, and 53% of funds considered in that sub-period analysis. This figure indicates that fund 209 has a vast network of commonalities, and is a significant contributor to the overall level of systemic risk in the hedge fund industry. A possible explanation for this could be that fund 209's fund value (alternatively, its Assets Under Management) is weighty share of the aggregate hedge fund industry.

Figures 7 and 8 show the autocorrelation function and average mutual information respectively of fund 209, and of the residuals obtained from regressing fund 209. These graphs are used to proxy the illiquidity risk of fund 209's return, as suggested in section 4. It is evident from the plot that fund 209 is prone to a significant degree of autocorrelation, and thus fund 209 is vulnerable to systemic illiquidity risk.

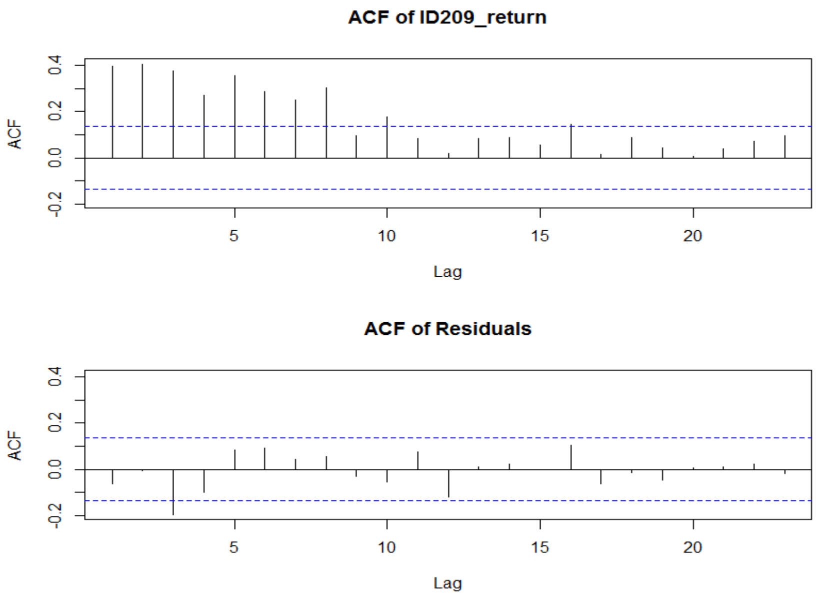

Figure 7: Autocorrelation function of fund 209 and its residuals

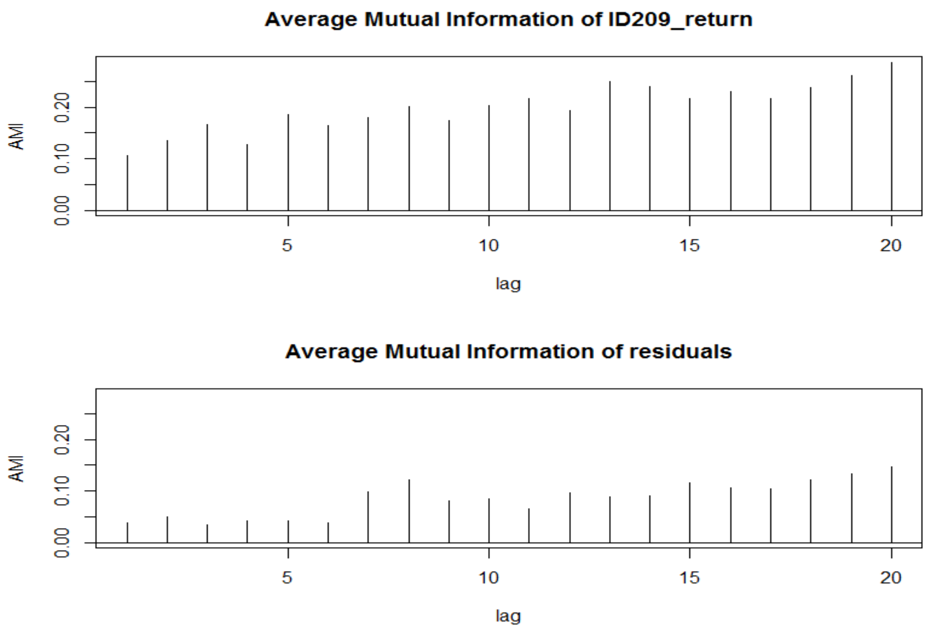

Figure 8: Average Mutual Information of fund 209 and its residuals.

Figures 9 shows the regime-switching model realizations, with the low regime observations plotted in black, while high regime observations are in red. It is evident from this plot that fund 209 enjoyed several sustained periods of high-regime expected returns, supporting the analysis at the start of this section. The average monthly fund return and standard deviation, respectively, in the low regime state are 1% and 20.5%, while the corresponding value for high regime are 1.9% and 14.2% - the high regime clearly has a better risk-return profile than the low regime. However, the low regime risk-return profile as well as the regime-switching behaviour could be a significant source of systemic risk if the probability of being in the low regime is too volatile (or too high) over time. Figure 10 plots this volatility. From the plot, it can be seen that in the years building up to the financial crises, at each time period, there was a large probability of low regime. After 2009, there was a sharp drop in the probability, and it has been consistently low since then.

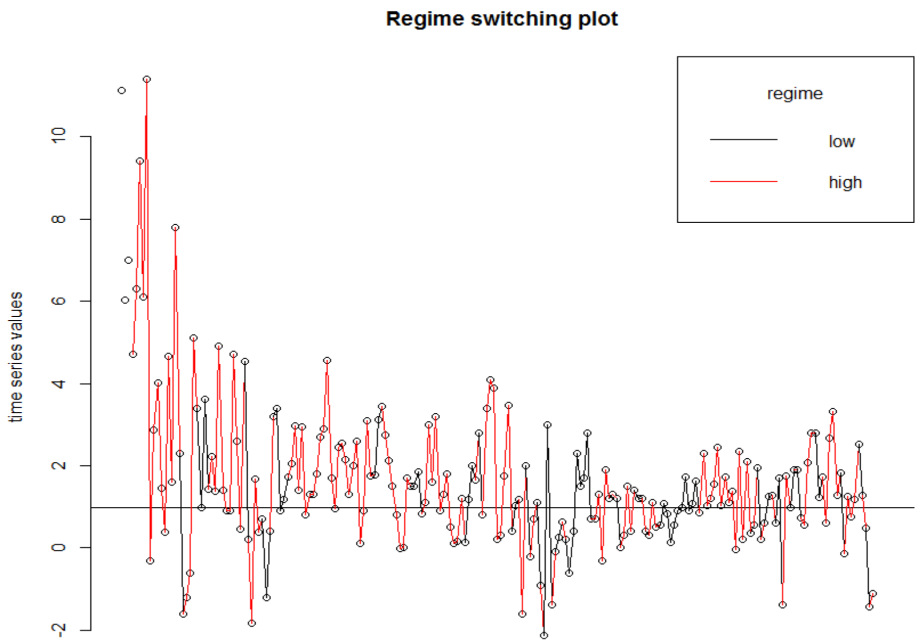

Figure 9: Regime-switching plot of fund 209's retutns (retuns as percentages)

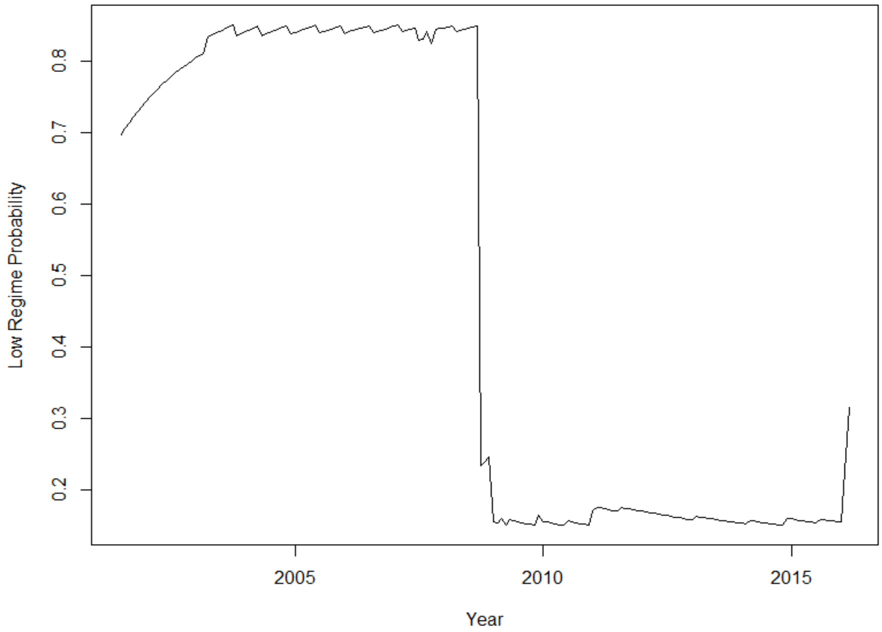

Figure 10: Rolling probability of transitioning into the low regime for fund 209

6. Discussion and conclusions

This study considered a sample of forty South African 'market neutral' hedge funds, and set out to investigate whether these funds actually were market neutral, as well as examine whether these funds were susceptible to systemic risks. Overall, the analysis in this study achieves what it purports to achieve.

The results from the analysis of market neutrality suggested that a noteworthy proportion of 'market neutral' hedge funds failed a test of neutrality. Compared to the results reported in Patton (2009)'s paper, the proportion of failures greater. However, unlike Patton (2009)'s paper, this paper did not smooth the hedge fund returns prior to analysing market neutrality, since Getmansky, Lo and Makarov (2004) show that smoothed returns can increase systemic risks, interconnectedness and hence commonality. These effects could potentially distort our results. Furthermore, an analysis of cross-fund Granger causality indicates that although very few combinations of funds exhibit two-way Granger causality, there are moderate network effects in the South African market neutral industry. Nonetheless, most of the funds exhibit significant degree of autocorrelation, which may be indicative of liquidity risks in the industry.

Overall, our results suggests that although the majority of market neutral hedge funds in South Africa are prone to moderate levels of risk, there may be some that are exposed to great levels of risk and understate these risks as they describe themselves as 'market neutral'. Such funds have the potential to introduce substantial contagion effects in the market neutral hedge fund industry. For this reason, there is a need for comprehensive hedge fund regulation such as those passed in South Africa, which required hedge funds to report their results.

The natural progression for further research suggested by the results of the analysis in this paper would explore possible ways to explicitly allow for the presence of systemic risks (in the financial industry), a fund's autocorrelation, and the network effects or commonality effects present. Additionally, the identification of significant systemic risks in this study would warrant a thorough analysis, to complement the tail risk measures introduced in this paper, using Extreme Value Theory of the tail risk faced by the funds in the database, in order to analyse the potential ripple effects of a market crash; such an analysis may include an approximation of the distribution of the "Jump" stochastic process describing the occurrence and frequency of very extreme events. Another possible suggestion for further research would involve identifying style-factors for a Principal Component Analysis of the hedge fund returns in our database, and hence ascertain the sources of risk in the market neutral hedge fund industry.

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Appendices

A Tables

Table 2: Showing the values of the autocorrelation function for the different funds at different lags

	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6
Return.0	0.12	0.05	0.15	0.19	0.25	0.15
Return.1	0.00	-0.10	0.12	0.25	0.11	0.03
Return.2	0.08	0.01	-0.02	0.02	0.14	0.10
Return.3	0.14	-0.03	-0.06	0.04	0.02	0.05
Return.4	-0.01	0.19	-0.14	0.03	-0.12	-0.16
Return.5	0.34	0.18	0.22	0.13	0.00	-0.15
Return.6	-0.17	0.09	-0.07	0.00	0.01	0.10
Return.7	-0.12	0.18	0.07	-0.04	-0.03	0.09
Return.8	-0.24	-0.12	0.07	0.11	-0.02	-0.10
Return.9	-0.16	0.28	-0.07	0.20	0.03	0.22
Return.10	0.18	0.15	0.34	0.21	0.23	0.22
Return.11	0.05	0.00	0.20	0.04	-0.12	-0.03
Return.12	-0.01	0.12	0.16	-0.03	-0.10	-0.05
Return.13	-0.25	0.24	-0.20	0.24	-0.14	0.01
Return.14	0.02	0.26	0.11	0.02	0.07	-0.02
Return.15	0.34	0.17	-0.15	-0.17	-0.10	-0.20
Return.16	0.22	-0.14	0.09	0.07	-0.02	-0.10
Return.17	-0.26	0.28	0.08	0.00	0.00	0.12
Return.18	-0.09	0.10	-0.06	0.02	0.10	-0.01
Return.19	0.15	0.20	0.08	0.07	0.13	0.11
Return.20	0.02	-0.09	-0.08	0.07	-0.19	-0.15
Return.21	-0.26	0.30	-0.23	0.11	-0.22	0.10
Return.22	0.34	0.42	0.30	0.31	0.07	0.13
Return.23	0.28	-0.15	-0.12	0.11	-0.07	-0.09
Return.24	0.28	0.15	0.11	0.08	0.03	0.04
Return.25	0.02	0.20	-0.20	0.13	-0.12	0.03

	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6
Return.26	0.08	-0.06	0.04	0.09	-0.09	-0.27
Return.27	0.07	0.14	-0.13	0.19	-0.15	0.06
Return.28	0.38	0.12	-0.09	-0.24	0.08	-0.02
Return.29	0.40	0.40	0.38	0.27	0.35	0.29
Return.30	0.15	-0.30	0.31	0.45	-0.15	-0.15
Return.31	0.20	0.42	0.00	0.09	-0.19	-0.10
Return.32	-0.06	-0.07	-0.37	0.22	-0.15	-0.18
Return.33	0.19	-0.24	-0.16	0.16	0.29	-0.10
Return.34	-0.16	0.03	0.25	-0.04	0.00	0.00
Return.35	0.38	-0.04	0.10	-0.01	-0.18	-0.14
Return.36	-0.22	0.07	0.02	-0.08	0.14	-0.18
Return.37	0.20	0.07	0.07	0.12	0.10	0.09
Return.38	0.01	0.26	-0.12	-0.01	-0.11	0.00
Return.39	0.15	0.03	0.06	0.02	-0.05	-0.08
Averages	0.07	0.10	0.03	0.09	0.00	0.01

Table 3: Showing the values of the average mutual information function for the different funds at different lags

	row.names	Lag.1	Lag.2	Lag.3	Lag.4	Lag.5	Lag.6
1	Return.0	0.43	0.44	0.50	0.42	0.44	0.42
2	Return.1	0.69	0.66	0.72	0.61	0.70	0.65
3	Return.2	0.77	0.69	0.77	0.77	0.71	0.59
4	Return.3	0.63	0.61	0.55	0.53	0.50	0.52
5	Return.4	1.19	1.09	1.06	1.15	1.13	1.16
6	Return.5	1.14	1.06	1.16	1.16	1.19	1.23
7	Return.6	0.44	0.47	0.48	0.52	0.43	0.54
8	Return.7	0.97	1.16	1.05	1.28	1.31	1.20
9	Return.8	1.11	1.06	1.02	0.99	0.94	0.99
10	Return.9	0.93	0.92	0.86	1.04	0.98	0.95
11	Return.10	0.78	0.73	0.79	0.78	0.66	0.78
12	Return.11	0.29	0.26	0.27	0.26	0.29	0.35
13	Return.12	1.27	1.26	1.38	1.21	1.34	1.39
14	Return.13	0.97	0.93	0.74	0.86	0.82	0.85
15	Return.14	0.69	0.66	0.67	0.74	0.56	0.54

	row.names	Lag.1	Lag.2	Lag.3	Lag.4	Lag.5	Lag.6
16	Return.15	1.29	1.23	0.85	1.04	1.15	1.33
17	Return.16	0.78	0.80	0.83	0.73	0.74	0.71
18	Return.17	1.63	1.63	1.63	1.49	1.63	1.59
19	Return.18	0.63	0.67	0.76	0.58	0.65	0.62
20	Return.19	0.48	0.48	0.47	0.41	0.46	0.47
21	Return.20	0.78	0.91	0.76	0.81	0.74	0.83
22	Return.21	0.89	0.89	0.84	0.70	0.73	0.62
23	Return.22	0.53	0.57	0.56	0.51	0.50	0.59
24	Return.23	1.30	1.08	1.00	0.97	1.07	0.98
25	Return.24	0.57	0.59	0.57	0.53	0.59	0.60
26	Return.25	1.13	1.13	1.08	1.18	1.15	1.21
27	Return.26	0.64	0.54	0.61	0.45	0.48	0.56
28	Return.27	0.90	0.85	0.70	0.93	0.99	0.87
29	Return.28	1.77	1.63	1.47	1.64	1.75	1.89
30	Return.29	0.38	0.41	0.39	0.35	0.42	0.38
31	Return.30	1.84	1.90	2.07	1.84	1.94	1.80
32	Return.31	1.00	1.11	1.06	0.85	1.17	1.07
33	Return.32	1.99	1.96	1.84	1.71	1.85	1.93
34	Return.33	1.14	0.97	0.97	1.11	1.34	1.16
35	Return.34	1.26	1.12	1.39	1.16	1.16	1.28
36	Return.35	0.66	0.80	0.50	0.61	0.54	0.59
37	Return.36	1.75	1.58	1.39	1.15	1.33	1.05
38	Return.37	0.64	0.81	0.75	0.69	0.61	0.68
39	Return.38	0.57	0.54	0.57	0.59	0.59	0.55
40	Return.39	1.12	1.26	1.24	1.15	1.29	1.12
	AVERAGES	0.95	0.94	0.91	0.89	0.92	0.92

B Figures and Graphs

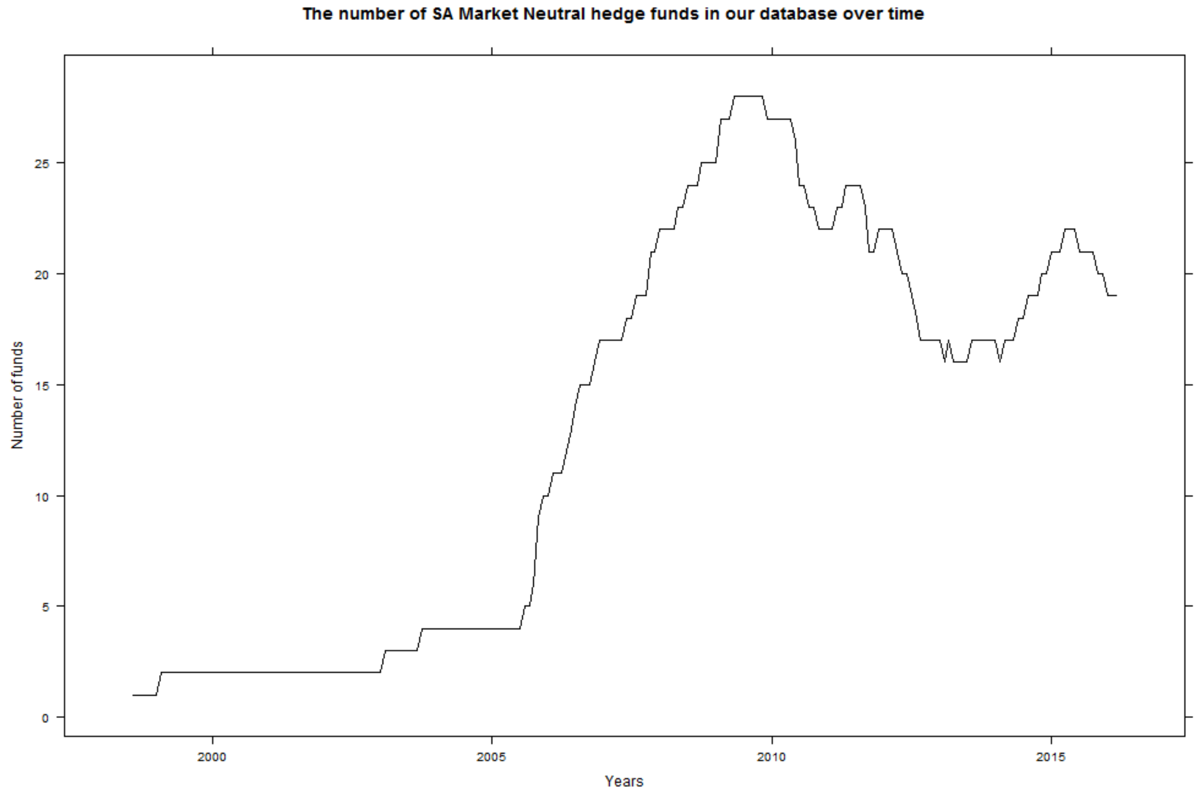

Figure 1: A graph showing the number of South African market neutral hedge funds contributing data to the database over the period of investigation.

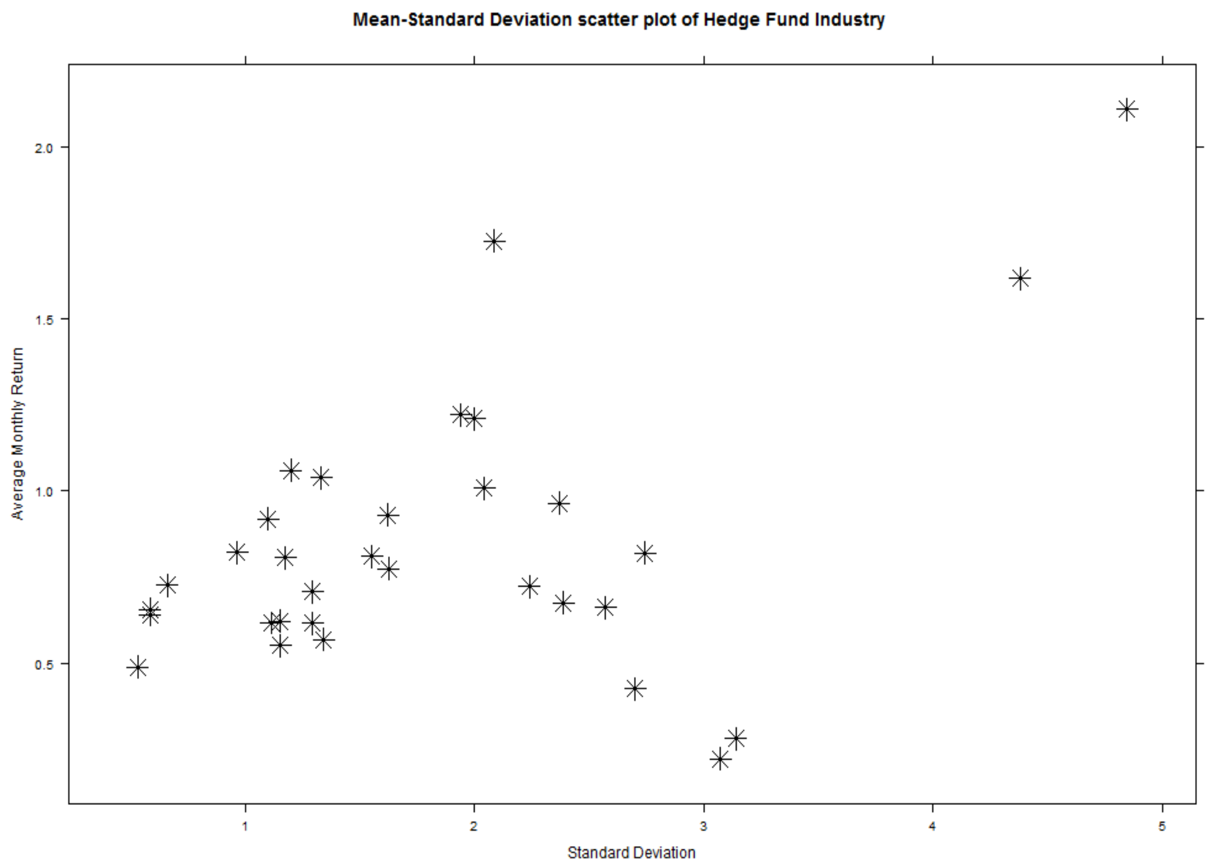

Figure 2: A graph showing the mean-standard deviation characteristics of the hedge funds in our database.

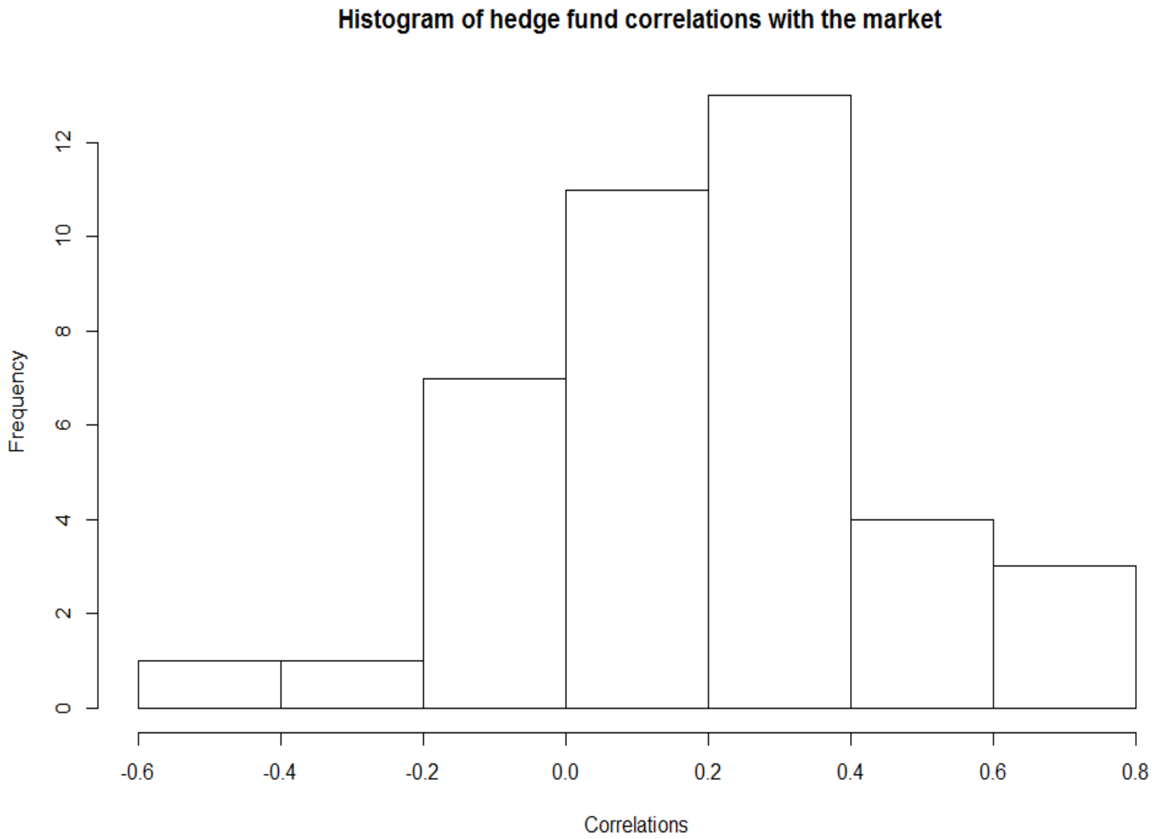

Figure 3: Histogram of hedge fund correlations with the market

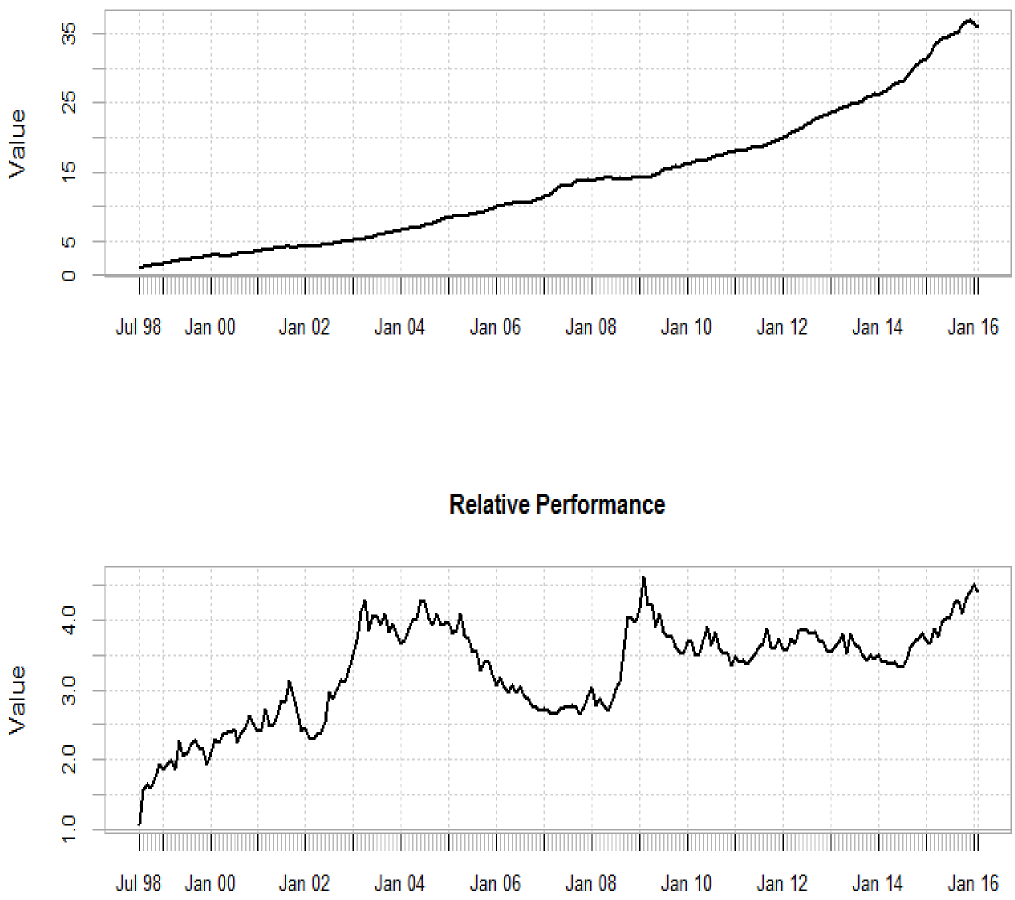

Figure 5: On the top half is a graph of the theoretical value over time of 1 unit invested in fund 209 at the beginning of July 1998; on the bottom half is a graph of the relative performance of fund 209 over the fund's lifetime.