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Gordon Institute of Business Science
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All-Weather Portfolio

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ABSTRACT

The Weather Effect, where stock returns are affected by investors as a result of weather-induced mood changes, has been found on various stock exchanges. Pizulito and Roncone (2016) argued that The Weather Effect could be a profitable market strategy.

This research report investigated the usefulness of this phenomenon for predicting future returns on the JSE and thereby creating an investment style, through the use of the style engine built by Muller and Ward (2013).

The research results revealed that the influence of the weather on stock returns is weak at best and cannot be used as an investment style. Previous concerns, as raised by Kim (2017) regarding data mining in providing evidence of The Weather Effect has been confirmed by this study.

KEYWORDS

Weather Effect; Behavioural Finance; Style-based investing

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DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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CHAPTER 1: INTRODUCTION TO RESEARCH PROBLEM

1.1 Background

The efficient market hypothesis (EMH) states that market equilibrium is based on expected returns (Fama, 1970), but requires that stock prices fully reflect all information. Hirshleifer (2015) added that for this hypothesis to be correct, the most important investors, at least if not all, must be rational in processing information. Saunders (1993) and Hirshleifer and Shumway (2003) published seminal work on the effects of mood on investors, which is in contradiction to the EMH, by analysing the correlation between the New York Stock Exchange (NYSE) and the daily cloud cover.

Behavioural finance is a relatively new field that studies irrational financial decisions made by people. The study of irrational choices is an attempt to apply psychology in the form of cognitive biases to finance. Hirshleifer (2015) proposed that if rational and irrational investors who miss value different components of fundamental payoffs, bet on stocks, then there would be a quick flow of wealth from the irrational investor to the rational. There is an assumption on this proposal which is that the market is frictionless, i.e. there is no transaction cost.

An arbitrage opportunity is presented in the form of weather, as this is one of the factors influencing mood and thereby cognitive biases. Goetzmann, Kim, Kumar and Wang (2015) found that institutional investors were affected by weather-induced mood and therefore no longer act rationally. The irrational stock price valuation implies that the asset prices vary from their fundamental value. If utilised correctly this could provide investment opportunities that supply superior returns. Pizzutili and Roncone (2016) raised the question whether a market strategy linked to the weather could be profitable.

Dong and Trembley (2011) discovered a hedge strategy that exploited weather-generated rules and utilised daily returns predictability to provide 25% out-of-sample gross profit. Furthermore, Novy-Marx (2014) found that specific investment styles performed better during cold weather in New York, while others did better in hot weather.

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It is plausible that The Weather Effect influences the different stock markets across the globe non-homogeneously, according to Pizzutilo and Roncone (2016). Pizzutilo and Roncone (2016) posited that in various geographical locations the weather varies and therefore the global population experiences significant variations in cognitive biases. Very little about The Weather Effect on the JSE from the available literature is present. Apergis and Gupta (2017), who found a statistically significant influence of New York weather on South African stock returns, proposed that research be performed to investigate if unusual weather can be utilised to predict South African stock returns.

1.2 Research Questions

Hirshleifer (2015) stated that more theoretical and empirical studies are required to develop behavioural finance. Analyses would include the investigation of financial decisions that were affected by feelings, and the implications of these effects. Goetzmann et al. (2015) investigated The Weather Effect and stated that there was growing theoretical literature on behavioural finance. Goetzmann et al. (2015) explained that the focus of these studies would be on the channels through which the mood of investors are influenced. The change in mood of investors would ultimately affect economic and financial market outcomes.

The assumption of behavioural finance, i.e. that mood affects investor's behaviour, has gained acceptance (Kaustia & Rantapuska, 2016). The recognition is a result of empirical studies that have connected stock returns with environmental variables, such as weather.

Apergis and Gupta (2017) performed an investigation of the influence of New York weather on the Johannesburg Stock Exchange (JSE). These authors noted that although a correlation was found, further research should be done on South African based investors, utilising South African weather data to add more weight to academic literature in this specific category. The current research study also assist in providing additional academic proof on specific geographical area of the subject, as recommended by Hirshleifer (2015).

The existing research into The Weather Effect has also raised concerns of correlation versus causation. Jacobsen and Marquering (2008) argued that the relationship between weather factors and stock market returns could just be ascribed to spurious correlations.

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Without additional support, it cannot be concluded that it is not the weather-induced mood shifts that caused the stock returns to move. It becomes necessary that further investigation is required to ascertain the validity of The Weather Effect. Kaustia and Rantapuska (2016, p. 24) proposed that although “mood-driven variation in day-to-day trading” is insignificant, investor sentiment as a result of The Weather Effect cannot be ignored.

In the Statistical community, Wasserstein and Lazar (2016) raised concerns about the “prevalent misuse” (p. 132) of *p*-values in statistics on which the existence of The Weather Effect proof resides. Lockett, McWilliams and Van Fleet (2014) also raised concerns of the *p*-value and proposed that alternative methods be used when testing for significance. Kim (2017) stated that the use of massive sample sizes, such as presented in the seminal work of Hirshleifer and Shumway (2003), produced spurious statistically significant results. Kim (2017) stated that the results of these studies are highly likely as a result of statistical Type I error. Kim’s (2017) investigation corresponded with findings by Krämer and Runde (1997), who performed analysis on the German Stock Exchange and local weather and found no correlation, further indicating that work performed by Saunders (1993) was a result of Type 1 error.

This current research report addressed the existence of The Weather Effect from an academic perspective. The report investigated whether it is possible to predict future returns based on weather factors. This would provide an alternative methodology to those that had been found to be problematic by authors such as Kim (2017). The methodology described in Chapter 4 is based upon Muller and Ward (2013) and presents a predictive model in forecasting weather expected returns.

Part of the outcomes of this research report is the investigation of the suitability of utilising The Weather Effect to solve a business problem. This research report investigated whether an investment style can be created from The Weather Effect to beat the market consistently. The creation of a style based investing technique requires investors to group stock based on shared characteristics (Wahal & Yavuz, 2013). The proposal in this research report is to arrange higher weather expected return stocks in a market beating portfolio.

Investment analysis is concerned with evaluating an investment for profitability and risk. The goal is to measure the suitability of an investment for a portfolio. Cumulus, an actively managed fund, has returned more than 960 percent over a period of 10 years

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(Fortado & Chiles, 2016). The fund ran unleveraged for a time, but investors of this fund preferred the higher returns of higher risk. The traders and expert meteorologists of this fund searched for discrepancies in the weather predictions and have found arbitrage opportunities.

Pizzutilo and Roncone (2016) proposed that to prove The Weather Effect, the weather's influence on all indices and stocks should be found; however, the business fraternity requires a solution to beat the market consistently. Furthermore, de Prado (2015) concluded that with machine-learning algorithms that allow for efficiently testing a broad variety factors and stock returns, it would produce all sorts of false claims. Kim (2017) stated that recent criticism of significance testing of empirical finance scrutinises earlier work of the effect of investor mood on the stock market.

The concerns raised by the academic society on significance testing requires the deviation towards other methodologies proposed by literature, and therefore a different methodology is described in Chapter 4. This research report utilised cumulative stock returns as a measure, as applied in Muller and Ward's (2013) study. From a business perspective, it was sought to determine whether a tradable all-weather portfolio can be created to outperform the market.

The two research questions raised by this research report addressed the existence of The Weather Effect and its tradability on the JSE. This research report has therefore increased the literature on behavioural finance by looking at the EMH of the JSE, which "is probably not as efficient as deemed by existing literature" (Apergis & Gupta, 2017, p. 12) and has added to the body of knowledge concerned with data mining. This research report has further provided an alternative investment strategy, although the results indicate that it is not a profitable alternative to existing styles.

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1.3 Research Objectives

The research objective was to investigate the effectiveness of utilising weather factors as a means to (1) predict future stock returns and to (2) create a portfolio that would consistently beat the market. Answering the two questions confirms the presence of The Weather Effect on the JSE which was previously claimed in the literature. More details of The Weather Effect's existence are presented in Chapter 2. The creation of a successful portfolio would mean that The Weather Effect could be considered as an investment style. This research project thereby attempted to address the question raised by Pizzutilo and Roncone (2016, p. 27) "was there a market strategy linked to the weather that would have been profitable in past years?"

Concerns about data mining, by means of significance testing, have been raised by the academic fraternity. The alternative methodology proposed in this research report provides a successful secondary analyses technique of The Weather Effect and its ability to be traded on the JSE.

The method proposed in this work was tested using time series data from the Johannesburg Stock Exchange (JSE) and data from the South African Weather Service (SAWS) over a period of 16 years. The results of the created portfolios were compared with the All Share Index (ALSI) as a benchmark.

The findings discussion, as presented in Chapters 5 and 6, adds to the body of knowledge of divergence from the EMH and the possibility of arbitrage thereby created. This arbitrage opportunity provides astute investors with an alternative to outperform the ALSI as a benchmark.

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CHAPTER 2: THEORY AND LITERATURE REVIEW

2.1 Behavioural finance

Behavioural finance investigates the irrational financial decisions people make by combining economic and financial theories with behavioural and cognitive psychological theories.

The premise for EMH is that investors rationally process information (Hirshleifer, 2015). The premise of behavioural finance is that people fall short of this hypothesis and that markets are to some degree inefficient. The EMH is challenged by various studies. Cortés, Dunchin and Sosyura (2016) found that sentiment varies across business cycles, as they discovered that decisions of financial officers more than doubled during the credit boom of the 2000s in the United States. A study performed by Siganos, Vagenas-Nanos and Verwijmeren (2017) proposed that divergence of sentiment, that is the distance between optimistic and pessimistic investors as measured by posts on Facebook, influenced trading volumes. Siganos et al. (2017) found that high divergence had high trading volume. Cohn, Engelmann, Fehr and Maréchal (2015) found proof of countercyclical risk aversion in the financial services sector.

Hirshleifer and Shumway (2003) proposed that receptive information processing is enhanced with improved mood. These two authors suggested that after positive events, people were more prone to accept new theories on the working of the stock exchange. Hirshleifer and Shumway (2003) referred to the 1990s and the positive mood of people in the United States, resulting in the internet bubble. These authors proposed that there was a correlation between the stock market and weather, or at least a weather factor, namely cloud cover.

Hong and Yu (2009) recommended that more models be investigated, which explains the positive contemporaneous correlation of trading activity, which was shown to be influenced by weather, and expected returns. Heterogeneous agent models predicted this would not be a positive case and according to Hong and Yu (2009), it became imperative to understand the heterogeneous agent models to predict asset prices.

Kaustia and Rantapuska (2016) proposed that individual investors sell stocks before vacation seasons and shorter breaks. The argument pertained to financing vacation

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consumption, thereby requiring a reduction of monitoring investments or a simple need for closure obtained by exiting the market.

Bassi, Colacito and Fulghieri (2013) argued that there exist a growing body of literature of behavioural finance, where the weather is a significant factor that drives risk aversion. This risk aversion could potentially affect stock prices.

Hirshleifer (2015) explained that behavioural finance had been considered a niche for the last three decades, and only a few of its influences have been mentioned in this literature review. From this section, it can be confirmed that EMH is challenged by various studies, and one of these contentious factors could be The Weather Effect.

2.2 Weather influences on mood

The effects of the weather on human behaviour have been found to be present in the literature. Research has indicated that a lack of sunlight experienced by an individual increase negative mood, depression, scepticism, and even melancholy (Cunningham, 1979).

Many academic studies have been performed to ascertain the influence of mood, emotions and feelings on judgement. A study conducted by Cunningham (1979) found that the amount of sunshine experienced by individuals influences their willingness to participate and assist an interviewer. Bassi et al. (2013) performed an experiment in the form of a psychological test on the mood of participants and proposed that good weather promote risk-taking behaviour, while bad weather increased risk aversion. A study performed by Parker and Tavassoli (2000) concurred with these findings. Cunningham (1979) found that other weather factors, including temperature, humidity and wind velocity influenced individual’s mood, but to a lesser extent.

The positive influence of sunshine on mood is explained from a medical perspective by serotonin level increases induced by sunlight (Van Der Rhee, De Vries, Coomans, Van De Velde, & Coebergh, 2016; Young, 2007). It is argued in contrast that low visibility, i.e. the distance at which an object can be discerned, induces melancholy and depression. Parker and Tavassoli (2000) argued that air movement, solar radiation and humidity influence consumption behaviours. They claimed that this is a result of thermoregulatory needs and preferences.

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Radua, Pertusa and Cardoner (2010) found that barometric air pressure influences psychotic depression. Their justification was the lack of production of tryptophan, an amino acid, which is a precursor to serotonin.

The increased risk-taking behaviour by individuals is evident in work performed by Cortés et al. (2016) who estimated that an extra credit of $91 000 per country day is approved on a sunny day. This has further implications as the authors found that loans approved on a sunny day had a 2.7% higher loan default rate (Cortés et al., 2016).

Furthermore, Lee, Gino and Staats (2014) found that bad weather increased the productivity of individuals. These authors argued that this increased productivity was as a result of good weather eliminating potential cognitive distractions. Lee et al. (2014) proposed that locating service operations in places of worse weather might be preferable.

Starr-McCluer (2000) found a correlation between weather and consumer spending. She stated that monthly fluctuations in consumer spending were often attributed to weather. During cold weather sales of durable goods are slightly increased. Parker and Tavassoli (2000) argued that temperature rise stimuli arousal potential, through the release of norepinephrine, which might influence consumption and utility of advertising.

Depending on geographical location, Keller, Fredrickson, Ybarra, Côté, Johnson, Mikels, Conway and Wager (2005) found that higher temperature either increased or decreased mood. This indicates an idiosyncratic effect of temperature, or weather factor, on mood.

Keller et al.'s (2005) study on Seasonal Affective Disorder (SAD) found individuals who spend more time outdoors, increased the relationship of temperature and barometric pressure to the individuals' openness of new information as a result of mood influence. This is intuitive, as exposure to the weather factors is what drives The Weather Effect, not that it exists somewhere else. SAD is a depression occuring seasonally, normally commencing in autumn or winter and ending in spring. The cause of SAD is a lack of serotonin created during the months of lower sunlight. Medical treatment for seasonal depression is to increase the patient's exposure to light (Cortés et al., 2016; Young, 2007).

SAD has been found to have correlations with returns on the stock market according to Kamstra, Kramer and Levi (2003). Daylight influences people's moods, which in turn is

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inversely correlated to risk aversion. Kaustia and Rantapuska (2016) found little evidence of SAD affecting the tendency to buy versus the tendency to sell, but they did find evidence that there is a positive influence on the total amount traded.

2.3 Weather Effect

An unchanging topic for superficial conversation is the weather, which influences people's moods as well as affects people's emotional and social behaviour. Hirshleifer (2015) proposed that weather influence on the stock market form part of behavioural finance.

The seminal work performed by Saunders (1993) and Hirshleifer and Shumway (2003) on the effects of sunshine on the mood of investors indicated a negative correlation between cloud cover and stock returns of the New York Stock Exchange (NYSE), i.e. more sunlight correlated with higher yields.

Hirshleifer and Shumway (2003) found that annualised returns for a perfectly sunny day in New York were 24.8% versus 8.7% on days with complete cloud cover. Hirshleifer and Shumway (2003) found that the logit regression model was statistically significant at a *p*-value of 0.0033. Saunders (1993) attempted to explain this weather influence through behavioural finance; that a sunny commute for a news editor might influence his preponderance for good news stories, which might, in turn, affect the market. This present correlation between weather impacting the stock market was coined The Weather Effect.

Subsequent research on The Weather Effect on various stock markets has proven that it is statistically significant. This body of research includes Keef and Roush (2002), Kamstra et al. (2003), Chang, Nieh, Yang and Yang (2006), Levy and Galili (2008), Yoon and Kang (2009), Kang, Jiang, Lee and Yoon (2010), Dong and Trembley (2011), Floros (2011), Lu and Chou (2012), Bassi et al. (2013), Schnieder et al. (2014), Smith and Zurhellen (2015), Schmittman, Pirschel, Meyer and Hackethal (2015), Goetzmann et al. (2015) and Apergis and Gupta (2017). It can be seen that the studies has been performed over a number of years and continue as this phenomenon is not fully understood. The reasoning for the extensive research into The Weather Effect is the effect it has had on various stock markets and multiple investors that have been investigated.

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Investor responses on emotion are not homogeneous, and therefore they would be influenced differently by the weather. In Saunders' (1993) seminal work, New York's cloud cover was seen as one of the "weather variable[s] that significantly affect mood"(p. 1338). In the subsequent work, various authors have shown that there are correlations between various weather factors and various global stock markets. As an explanation for this, Pizzutilo and Roncone (2016) proposed that a stock market might be idiosyncratic and therefore the results of one stock exchange might not be transferable to another. This was confirmed by Dong and Tremblay (2011) who proposed that weather factors be "contingent on geographical and seasonal environments"(p. 7).

Hirshleifer and Shumway (2003) performed their analysis of The Weather Effect on 26 stock exchanges across the globe between 1982 to 1997 and found that in countries with low transactional costs, The Weather Effect provided a profitable advantage. Hirshleifer and Shumway (2003) mentioned that studies with significant results were more likely to be published, therefore published articles were more likely to have significant meaningless results. The deseasonalised cloud cover was used as investor mood proxy by Goetzmann et al. (2015), who found that on the Dow Jones Industrial Average (DJIA) the increased likelihood of perceived overpricing was approximately 3%.

Smith and Zurhellen (2015) extended the study performed by Hirshleifer and Shumway (2003) to 2013 and found a decreasing influence of The Weather Effect. Smith and Zurhellen (2015) argued that it was a result of trading becoming decentralised, and hence traders would experience different weather factors.

Kang et al. (2010) and Lu and Chou (2012) found that weather failed to influence stock returns on the Shanghai Stock Exchange, but rather that it affected volatility. Kang et al. (2010) found that during sunshine periods, investors were more likely to engage in trading. Yoon and Kang (2009) found substantial evidence of The Weather Effect before the Asian market crisis, but none after; this was ascribed to the abolishment of local traders only as international traders were also present. These findings are in line with the arguments posited by Smith and Zurhellen (2015), with different individuals experiencing different weather factors.

Schneider (2014) found that atmospheric pressure was the most significant contributor to The Weather Effect on German cities. Schmittmann et al. (2015) found that German retail investors purchased more than they sold in weather with higher-than-usual temperature, air pressure and lower-than-usual cloud cover. During times of lower-than-

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usual temperature, air pressure and higher-than-usual cloud cover retail investors performed more absolute trades. Schmittmann et al. (2015) argued opportunity cost as a cause, in that during good weather retail investors prefered to spend time performing activities outside. Lee et al. (2014) found that desire to perform outside operations decreases with lousy weather, thereby eliminating potential cognitive distractions and thus increases productivity. It has therefore been argued that the "positive impact weather has on human sentiment" (Schmittmann et al., 2015, p. 1145) is the cause for The Weather Effect.

Keef and Roush (2002) found that wind significantly influenced daily stock returns on the New Zealand Stock Exchange. The cloud cover was found to have no influence while temperature only had a small impact on New Zealand's Stock Exchange returns. These authors proposed that this was attributed to the wind effect on daily life in "Windy Wellington" (Keef & Roush, 2002, p. 61) in New Zealand.

Pizzutilo and Roncone (2016) argued that different climatic conditions have had varying psychological traits imprinted on groups around the globe. Hirshleifer and Shumway (2003) found that the mean cloud cover in Taipei is 5.55, in New York, it is 4.95, while it is 3 in Johannesburg. The argument can be made that this difference in a climatic condition would lead to a difference in the effect on the investor. The OLS regression of The Weather Effect shows that the t-stat of Taipei is -0.97, New York is -1.28 and Johannesburg is 0.48.

This non-homogeneous effect has been revealed by empirical evidence from Taiwan in a study performed by Chang et al. (2006). Chang et al. (2006) showed that The Weather Effect was present, but that a combination of temperature and cloud cover had the most substantial influence on stock market returns. The findings also concluded that there was a presence of SAD during the autumn and winter season and suggested that extended hot summers or the intense cold weather would increase impatience or agitation, and hence influence the stock market.

As cities or countries have non-homogenous responses to weather, so too have different investors. It could also be assumed that individual investors might act rationally, but a group of individuals work non-rationally often termed "the herd mentality". Kaustia and Rantapuska (2016) argued that individual investors were more easily influenced by mood than institutional investors, which typically involved the decision of many individuals. From the behavioural finance perspective, it can be assumed that some investors would

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act more rationally than others. Levy and Galili (2008) proposed that specific subgroups of investors were more likely to be influenced by The Weather Effect.

Loughran and Schultz (2004) and Schmittmann et al. (2015) believed that retail investors would be more influenced by external factors such as moods than that of institutional investors. Levy and Galili (2008) argued that young, male and poor investors were more likely to be net buyers of shares on days with ample cloud cover. Levi and Galili (2008) ascribed this tendency of the mood of the investors to be more prone to gambling. Bassi et al. (2013) proposed that weather impact risk-taking behaviour through its influence on attitude. Goetzmann et al. (2015) found that the weather-induced mood affects the investors' perceptions about market pricing.

As there are investors who differ from each other by the extent of being influenced by The Weather Effect, it is understandable to expect that there would also be differences in what they invest in. Smith and Zurhellen (2015) found that sunshine influences lightly capitalised stocks the most by evaluating DJIA, CRSP value-weighted index and the CRSP equal-weighted index. Schnieder et al. (2014) found the higher performance of a hedge portfolio consisting of technology stocks and small-cap stocks portfolios. Loughren and Schultz (2004) performed a logit regression and found a significant negative relationship between a value-weighted NYSE/Amex/NASDAQ CRSP index and New York cloud cover but found no weather-return relationship on equally weighted indices.

Loughran and Schultz (2004) raised concerns that the weather experienced by the investor is not the same as the weather of the specific city or country's stock exchange. They used the example that the weather of the stock exchange and investors in Brussels or Copenhagen might be the same, but in cases such as Sydney or Rio de Janiero, this is unlikely the case due to country's geography. Loughran and Schultz (2004) therefore used weather near a company's headquarters to evaluate The Weather Effect on its stock but found no evidence of any relationship. Schneider (2014) found that shares with a higher degree of domestic ownership and higher associated risk were more affected by The Weather Effect. Lu and Chou (2012) argued that the influence of The Weather Effect is less in an order-driven market, where investors directly submit orders from dispersed locations, than a quote-driven market as these orders are from the same geographical area.

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Loughran and Schultz (2004) postulated that a newer firm, such as those listed on the Nasdaq, would more likely have investors close to the company's headquarters, than a more seasoned NYSE firm. Loughran and Schultz (2004) argued that the NYSE firm's ownership would be more geographically dispersed.

From the literature study, it can be concluded that there is statistically significant evidence of The Weather Effect. Hirshleifer and Shumway (2003) proposed further research in momentum and overreaction as a result of the mood of the investor. Goetzmann et al. (2015) recommended future work into weather-induced mood-influencing groups of economic agents, other than institutional investors, which could in turn influence the stock market. Pizzutilo and Roncone (2016) suggested further investigation of diversification, by investing in various stock markets. Cortés et al. (2016) stated that their methodology could be utilised to test the effects of sentiment on economic agents, other than those they had already evaluated. They proposed the evaluation of an analyst's action by using a time stamp to compare it with the analyst's action.

Another proposal is the effect of daily sunshine on a professional macroeconomic forecaster. Pizzutilo and Roncone (2016) proposed that stock trading and indices should be addressed when investigating The Weather Effect, as the outcome would be pervasive. The weather effect should, therefore, influence stock trading activity and indices, and not be limited only to one.

2.3.1 Season adjusted Weather effects

The seminal work performed by Saunders (1993) analysed absolute values of the weather factors, i.e. cloud cover. However, the deseasonalised weather effect was found to be prevalent in literature thereafter. This is typically done by taking The Weather Effect of the day, for instance, the total sky cover (SKC), and then subtracting the weather factor average of that month in which it falls, i.e. the SKC of the month to which it belongs. This is then considered the season adjusted or deseasonalised weather factor.

The utilisation of the deseasonalised weather factor was used by Cortés et al. (2016) who argued that by using deseasonalised cloud cover, they would be excluding the contribution of cloud cover to seasonal patterns such as variation of daylight which could lead to SAD. The second reason for using the deseasonalised weather factor was to remove intra-year economic cycles. Goetzmann et al. (2015) argued that investors may

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assess the weather of a particular day in relation to the season's average, thereby capturing the unexpected component of that day's weather.

Kaustia and Rantapuska (2016) proposed that weather-induced day-to-day mood changes do not exert a major influence on the investors' trading activities. These authors did, however, state that although it might not be found to be statistically significant on a day-to-day basis, the influence thereof might still be prevalent.

Schmittmann et al. (2015) stated that according to intuition, The Weather Effect is potentially stronger if the weather conditions, either good or bad, are prevalent over several days. This is explained with the high level of the autocorrelation of the weather variables. Schmittmann et al. (2015) expected that the impact of The Weather Effect would be more noticeable when measuring over a number of days. These authors coined the phrase "momentum in weather". They utilised the momentum in weather in their robustness checks. This momentum concurred with findings of depression onset with a delay of one month for hospitalisation of patients with depression (Radua et al., 2010).

Kang et al. (2010) found that the weather affected the volatility and returns on the Shanghai Stock Exchange by utilising a 21- and 31-day moving average. Yoon and Kang (2009) also used 21- and 31-day moving averages. The reasoning is that the weather variables that were chosen, namely temperature, humidity and cloud cover are highly seasonal. Yoon and Kang (2009) argued that using moving averages and its standard deviation to adjust overcomes these problems.

Pizzutilo and Roncone (2016) proposed that weather in the morning has the most considerable influence on humankind. They argued that other factors may influence a person's mood during the course of the day. They also explained that an individual has contact with weather in the morning, and not during the entire day as individuals generally work in offices. This is similar to the studies of Hirshleifer and Shumway (2003) and Smith and Zurhellen (2015) who investigated the cloud cover between 05:00 am and 08:00 am.

2.3.2 Analysis of Weather Effect

In most cases of the research concerning The Weather Effect, the authors either used ordinary least square (OLS) or generalised autoregressive conditional heteroskedasticity

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(GARCH), with the latter only prevalent in the last few years. The reasoning for the move towards the utilisation of the GARCH approach was autocorrelation and heteroscedasticity found by various authors. Krämer and Runde (1997) were the first to identify the possibility of heteroscedasticity in The Weather Effect as they raised concerns that the lack of monotonic relationship between cloud cover and stock returns could lead to the potential of data mining. Schmittmann et al. (2015) stated that complication arises in the delayed or cumulative responses to demeaned weather as a result of the high degree of autocorrelation within the predictor variable.

For the analysis of The Weather Effect, Lu and Chou (2012) used OLS of deseasonalised SKC and daily indices returns.

$$\mathrm{R_{it}} = \alpha_\mathrm{t} + \beta_\mathrm{i}\mathrm{R_{it-1}} + \beta_\mathrm{ic}\mathrm{SKC_{it}} + \varepsilon_\mathrm{t} \qquad \text{Equation (1)}$$

Where ε_t is the error term, *SKC* is the deseasonalised SKC, β_{ic} is the beta, α_t is the alpha at day *t*.

For the OLS to hold, some fundamental assumptions were made. One of the premises according to Kenkel (1996) is that of homoscedasticity, which is that the distribution would have the same variance σ_t^2. This hypothesis would be violated if the dispersion about the regression line would vary with the magnitude of the explanatory variable, i.e. be heteroscedastic.

The second assumption which has to hold is that of serial correlation. This hypothesis, according to Kenkel (1996), requires that the error terms are independent of each other. This is particularly a problem when studying time series data, i.e., data which has been ordered chronologically (Kenkel, 1996).

Saunders (1993) denied the existence of heteroscedasticity or autocorrelation. Hirshleifer and Shumway (2003) accepted that heteroscedasticity was prevalent, but stated that heteroscedasticity across panels and autocorrelation within longitudinal data had a small effect on the interference.

The existence of autocorrelations is in line with the findings of Agiray (1989). He stated that many studies exhibited some autocorrelation in time series analysis of daily stock

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returns, but which are too small to trade. Agiray (1989) argued that there is a significant level of dependence in time series of daily stock returns, i.e. from where the autocorrelation originates as today's price is influenced by yesterday's price.

Agiray (1989) proposed the GARCH model to aid in further understanding of the relationship between volatility and expected returns. Agiray (1989) found that monthly stock returns were not as leptokurtic as daily returns; he stated that monthly returns were independently normally distributed ("sticky white noise"), unlike daily returns which were autocorrelated. The utilisation of the GARCH model provided for a "more flexible lag structure" (Bollerslev, 1986, p. 308) providing advantages for a learning mechanism.

The GARCH model can be expressed in the form of the process is expressed as an autoregressive process of order *k*

$$\mathrm{R_t} = \alpha_0 + \sum_{i=1}^{k} \beta_i \mathrm{R_{t-1}} + \delta\sigma_t^2 + \varepsilon_t$$ Equation (2)

Where σ_t^2 is the variance, ε_t is the error term, β_{ic} is the beta, α_t is the alpha at day *t*. From this formula it is possible to identify the autocorrelation factor and the heteroscedastic factors, not prevalent in the OLS model of equation 2. One of the assumptions includes the use of a continuous set of data (Jacobsen & Marquering, 2008).

Authors who utilised the GARCH, or a variation thereof, on The Weather Effect included Chang et al. (2006), Kang, Jiang, Lee and Yoon (2010), Floros (2011), Chang, Nieh, Yang and Yang (2006). Chang et al. (2006) found autocorrelation on daily stock prices in Taiwan. Chang et al. (2006) argued that non-linear models would be better specified for the weather factor stock return relationship as stock returns are stationary time series.

A general trend found throughout the literature was the inclusion of dummy variables in an attempt to exclude for endogeneity. The stock market anomalies such as the Monday and the January effects (Goetzmann et al., 2015) were attempted to be eliminated. This is standard practice in statistics with particularly monthly dummy variables (Kenkel, 1996).

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2.3.3 Weather Investment styles

Wahal and Yavuz (2013) argued that investors classify stocks into styles based on common characteristics, which simplifies decision making in an attempt to generate return predictability. Muller and Ward (2013) performed an investigation into these styles and found that momentum, earnings yield and cash flow to price provided superior returns on the JSE. Wahal and Yavuz (2013) argued that for an investment style to be acceptable, it requires that the style is generally accepted and utilised by investors, it must span a multitude of asset classes and assets within a style must be mutually exclusive. Pizzutilo and Roncone (2016) concluded their study by questioning whether The Weather Effect can be utilised to be a profitable market strategy.

Novy-Marx (2014) found that specific investment styles, some of which were investigated by Muller and Ward (2013), performed better during cold weather in New York. These included small cap strategies, value strategies, strategies based on long-run reversals, asset growth, and asset turnover. Novy-Marx (2014) stated that hot weather provided better returns for earnings-related styles; "return on assets, earnings-to-price, gross margin, Piotroski's F-score and earnings momentum" (p. 139). Novy-Marx (2014) argued that New York City's weather influences the trading behaviour of investors and that there is a predictability in investor behaviour.

Autocorrelation, on which a great deal of The Weather Effect has been based, has been found not to be tradeable. On its own, the magnitude of autocorrelations and associated volatility are too small to profit from in-trading rules, according to Agiray (1989). What is important to note is that the autocorrelation is for daily stock returns. Agiray (1989) did not find any autocorrelations between monthly returns.

Although it is argued that autocorrelations are too small to trade, Dong and Trembley (2011) found a hedge strategy which exploited weather-generated rules and utilised daily returns' predictability to provide 25% out-of-sample gross profit. An OLS regression coefficient was used by Dong and Trembley (2011) who took a long or short position in counties which had the highest or lowest weather predicted returns. Their portfolio was rebalanced daily.

Schneider (2014) proposed a market timing technique whereby the autoregressive model of the first order by using the barometric pressure to decide whether to go long or short on an index the following day. They investigated various indices, but their analysis

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revealed a 298% return between 1998 and 2007 on the DAX technology index when investing and holding during the period provided a -0.05% return. Schneider (2014) argued that break-even transaction costs are lower than the gains produced by the trading strategy.

Hirshleifer and Shumway (2003) stated that weather strategies would require frequent trading in which reasonably moderate trading costs would eliminate the benefits of the weather. These authors proposed that investors should not trade on this, but instead become aware of their own mood and not be influenced by it. From this, it can be concluded that there is evidence that The Weather Effect has been found to be an investment opportunity in the global market.

Kamstra, Kramer and Levi (2003) proposed a trading strategy by utilising SAD. They recommended investing in the northern hemisphere during fall and winter and moving the funds to the southern hemisphere during its fall and winter. They suggested to use Sweden and Australia, which provided a 7.9% superior return instead of an invest and hold strategy in both. This proposed plan would, in fact, be betting against SAD.

Fortado and Chiles (2016) referenced Cumulus, and actively managed fund, which has returned more than 960 percent over a period of 10 years. The fund ran unleveraged for a time, but investors of this fund preferred the higher returns of higher risk. The traders and expert meteorologists of this fund investigate discrepancies in the weather predictions and find arbitrage opportunities.

The hedge strategies and timing strategies were the only cases found in the literature review that was presented in this Chapter. None of these investment styles was inspected on the JSE, providing an opportunity for research.

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2.4 Level of statistical significance

The null hypothesis significance testing (NHST) is entrenched in quantitative financial research. In this type of research, the most widely used value as a measure for accepting or rejecting the null is a *p*-value of 0.05 (Lockett et al., 2014). However, Wasserstein and Lazar (2016) stated that the statistical community has been uneasy about the issue of reproducibility and replicability of scientific conclusions. Concerns about the "prevalent misuse" (Wasserstein & Lazar, 2016, p. 132) of the statistical significance as sole criteria of the importance of a finding has been raised. Wasserstein and Lazar (2016) proposed that alternative methods be used when testing for significance.

In a survey performed by Kim and Ji (2015) they observed a substantial evidence to publication bias to statistically significant results. These authors stated that conventional significant levels are exclusively used, without consideration for sample size, the power of the test and expected losses. In their study, they excluded reviews based purely on time series analysis and those that utilise non-linear or Bayesian estimation methods. Kim and Ji (2015) proposed that finance researchers carefully select levels of significance, instead of mindlessly employing conventional levels.

Lockett et al. (2014) stated that NHST is dominant due to four primary reasons; convenience plays a major role, large-scale data collection is rewarded, novelty is valued over replication, and finally, there is an illusion of scientific rigour created. There is a fixation with large datasets by the scientific community, which merely increases the probability of statistically significant results. As discussed above, statistically significant effects are more likely going to be published, hence the reservations of data mining. Lockett et al. (2014) proposed that the manner in which management research could change is that in quantitative analysis the practice of NHST should be de-institutionalised.

Kim (2017) stated that the use of massive sample sizes, such as the ones used by Hirshleifer and Shumway (2003), produces spurious statistically significant results. This has severe implications for studies that were conducted into The Weather Effect, as expressed in Section 2.3. Kim (2017) stated that past Weather Effect studies are prone to be spurious and provide an outcome of Type I error. This error occurs "when we incorrectly reject the null hypothesis that is true" (Kenkel, 1996, p. 392).

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The Weather Effect has been investigated by other authors who are not convinced by the claims that this is another capital market anomaly, but instead data mining. Gerlach (2007) argued that, although finding statistically significant results of temperature effect at 10% level, these are as a result of data mining and would unlikely persist out of sample. Authors who agreed with this outlook include Krämer and Runde (1997), Trombley (1997), Loughran and Schultz (2004), Jacobsen and Marquering (2008), Pizzutilo and Roncone (2016) and Kim (2017).

Krämer and Runde (1997) found no correlation on the German Stock Exchange and raised concerns that the way in which the null hypothesis is phrased might influence the results. However, they found that at 100% cloud cover there is evidence of The Weather Effect. Trombley (1997) found little correlation on the NYSE which only appears during certain months of the year. Jacobsen and Marquering (2008) concluded from aggregated data that there is “little empirical evidence that weather-induced mood changes of investors influence stock prices” (p.540). Jacobsen and Marquering (2008) found fault with the findings of Kamstra et al. (2003) in that Kamstra et al. (2003) failed to substantiate the claim that SAD alone causes the risk aversion.

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2.5 Johannesburg Cloud Cover

It was found in the literature reviewed that The Weather Effect has been investigated on the JSE by some authors; Hirshleifer and Shumway (2003), Kamstra, Kramer and Levi (2003), Jacobsen and Marquering (2008) and Apergis and Gupta (2017).

Johannesburg's mean cloud cover of 3 is the lowest of the sample used by Hirshleifer and Shumway (2003). Compared to that of 4.95 in New York, which is used in most of the studies. As indicated earlier, stock exchanges are idiosyncratic, and therefore, the influence of weather effect cannot be the same. This is what was found by Hirshleifer and Shumway (2003), as a positive correlation between cloud cover and stock returns was found for the JSE of 0.004, while there is a negative return found on NYSE, -0.007. This then raises the question of whether South African investors are not influenced by a lack of serotonin levels on cloudy days, as they experience sufficient sunlight.

Apergis and Gupta (2017) performed an analysis on the JSE. However, their investigation was on New York weather and the JSE stock returns. They found a statistically significant negative effect. This correlates with Goetzmann et al. (2015) who also analysed investors who are not located at the New York stock exchange.

In a study slightly different from the ones addressed above, Kamstra et al. (2003) investigated SAD, and controlled for temperature, rain and cloud cover, on various stock exchanges. Kamstra et al. (2003) found that there is an annual return of 17.5%, significant at the 10% level, on the JSE as a result of SAD, compared to an annualised return of 14.6%. The Weather Effect on South Africa, with significant and reverse temperature and SAD on South Africa, was found (Jacobsen & Marquering, 2008).

The research on Johannesburg indicated a positive correlation with returns and Johannesburg cloud cover. This is in contradiction with the hypothesis of behavioural finance, due to the reduction of serotonin levels of Johannesburg investors.

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2.6 Conclusion

From the literature study as presented above, it can be concluded that there is evidence of The Weather Effect on various markets across the globe. The Weather Effect is also not influenced by only one weather factor, but on the entire spectrum, depending on the region of the exchange. The methods which were utilised for testing of The Weather Effect has been criticised as the assumptions of the tests employed does not hold in all cases.

From The Weather Effect, some studies have investigated whether there is a possible trading advantage this would provide. There is research to indicate that this is a possibility. However, no analysis was found by the author on whether creating an all-weather portfolio on the JSE was performed.

Loughran and Schultz (2004) on p363 stated that “we would not dismiss the possibility that the relationship between cloud cover and New York stock exchange is spurious”. Therefore, further investigation into the relationship is required.

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CHAPTER 3: HYPOTHESIS

The research work pertaining to this research study explored The Weather Effect on the JSE. Two parts have been addressed, namely the academic question of the existence thereof and the business case regarding the tradability. The benchmark to which the tradability was measured was selected as the ALSI as this is a measure of the market. The two research questions were addressed as NHST, but also further interrogated, which is aligned with the recommendations from Lockett et al. (2014), however only the hypothesis testing is described in this Chapter.

The question is specific to the JSE, as Pizzutilo and Roncone (2016) found the idiosyncratic behaviour of stock markets, and utilises daily closing prices of shares at the end of the month. The current research study investigated aggregated share prices monthly at the portfolio level and not at industry or index level, as with other weather investment styles.

The continuous successful inclusion of shares into a portfolio, which consistently beat the market, could constitute an investment style. This method of share inclusion was considered to be a good investment style with portfolio result resulting in a broad cross-section of returns. The best portfolios, therefore, had to outperform the benchmark while the worst should not. The portfolios that beat the market for successful completion is Weather1 as this is the portfolio with the highest expected returns from the ranked portfolios.

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3.1 Research Question One

Question one investigated whether The Weather Effect can successfully be utilised to predict future returns of the all-weather portfolio. The forecasted portfolios were calculated by utilisation of weather predicated stock returns. Only Forecast1 will be used as research analysis as the business question would require the use of the highest predicted returns.

The null hypothesis states that the difference between monthly returns of the forecasted portfolio with highest expected returns with the realised returns is zero.

$H_{1,0}$: $\mu_{d,1} = 0$ The difference in population means is zero

$H_{1,A}$: $\mu_{d,1} \neq 0$ The difference in population means is not zero

3.2 Research Question Two

Question two investigated whether a portfolio of shares created by utilising The Weather Effect performed the ALSI. The created portfolio consisted of stocks that had the superior predicted returns.

The null hypothesis states that the difference between expected monthly returns of the weather portfolio and the ALSI is zero.

$H_{2,0}$: $\mu_{d,2} = 0$ The difference in population means is zero

$H_{2,A}$: $\mu_{d,2} \neq 0$ The difference in population means is not zero

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CHAPTER 4: RESEARCH METHODOLOGY

This research study was aimed at examining whether The Weather Effect was present on the JSE and whether it could be used as an investment style. Claims have been made, as evident in the literature reviewed in Chapter 2, that The Weather Effect has been used, in some aspect, to provide superior returns (Dong & Tremblay, 2011; Fortado & Chiles, 2016; Novy-Marx, 2014; Schneider, 2014).

An attempt was made to create an all-weather style that could consistently beat the market. Muller and Ward (2013) examined the effects of style-based investing on the JSE over the period between 1986 and 2011, which was the basis for the research methodology in this thesis. This research report included work of Schneider (2014) and proposed a trading strategy utilising a predictive model whereby the previous weather factor, although only pressure was employed by them, to predict the following day's returns. The model proposed in this research report includes six weather factors; barometric air pressure, wind speed, cloud cover, daily rain, maximum temperature and minimum temperature.

The investigation period was from 31 December 2001 until 31 March 2017. Performing the analysis by starting the review at the end of a year is the general trend in the literature (Muller & Ward, 2013). This 16 years of analysis is in line with studies by Dong and Tremblay (2011) and Schneider (2014) who performed their analysis of 19 years and 15 years, respectively. The time period also includes the market crash of 2008 which provides a glimpse into the performance of the style during all aspects of the market.

4.1 Research Design

With the study running over 16 years and by means of quantitative data from the JSE, a longitudinal study was performed. The reasoning is that this study requires tracking performance over time.

The deduction approach to research was taken as there is a theoretical hypothesis, as indicated in Chapter 2, which was tested on the JSE. The conceptual hypothesis is grounded in behavioural finance theory, expressed as The Weather Effect, which has been investigated by Schmittmann et al. (2015). A quasi-experimental time series design

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was used, as data was presented graphically and was analysed using the graphical time series approach, as proposed by the work performed by Muller and Ward (2013).

The reason that this is seen as an experiment is that one of the independent variables to be manipulated is the stocks within the all-weather portfolio. The dependent variables, the portfolio return, were influenced by the independent variable. Hypothesis testing was performed as one of the evaluation measures in a quantitative manner to determine if statistical differences between monthly rebalanced portfolio returns and the benchmark exist.

The study also attempted to address more weather factors, than was presented by previous work, as stock markets are idiosyncratic (Pizzutilo & Roncone, 2016). Therefore what would be considered to be weather which might cognitively influence investors in in one area might not be the same for others, and this study was limited to the JSE. Previous work on the JSE has indicated a positive correlation between stock returns and cloud cover, as shown in Section 2.5.

A mono-method was utilised as only quantitative data is applicable in this study and there was no need to change approaches or strategies. Furthermore, in the seminal work of Saunders (1993) and similar studies by Hirshleifer and Shumway (2003), the mono-method of quantitative data was utilised. Mixed methods were performed at later dates, an example thereof is the study by Goetzmann et al. (2015). The mixed method studies attempted to address The Weather Effect at a granular level, identifying individual investors. Pizzutilo and Roncone (2016, p. 27) argued that this mono-method might not be the “most correct way to solve the puzzle”, but it is the “best approach in practical terms”.

4.2 Population and sample

The population of this study was South African companies on the JSE during the research period. This study was limited to JSE as The Weather Effect is idiosyncratic, according to Pizutilo and Rincone (2016). It would be possible to utilise this methodology on other stock markets, thereby indicating its suitability as an alternative to NHST.

The samples that had been utilised was the ALSI, which consists of the top 160 shares. The ALSI represents 99% of the market capitalisation (Muller & Ward, 2013). The

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reasoning for not utilising the entire JSE of about 440 shares is the problem concerning illiquidity. Trading in these shares becomes difficult, and with rebalancing monthly, the illiquidity premium would influence the results. During the simulation, it is assumed that the shares were traded immediately at closing price values. Smith and Zurhellen (2015) found that lightly capitalised stocks were influenced more by The Weather Effect. No survivor bias was included possibly augmenting the results. Therefore all companies entering and exiting the index were considered.

4.3 Unit of Analysis

The primary unit of analysis selected for this study was different from the two research questions. The unit of analysis is the statistical monthly returns for the first research question. Cumulative share returns of the weather portfolios were selected as the primary unit of analysis for the second research question. The various share returns would be evaluated regarding percentage change over the invested period compared to the benchmark index and the ALSI in the form of the J203T All-Share with dividend capitalised (Webb, 2014).

Macroeconomic fluctuations and seasonal effects, such as the 2008 market crash and the January effect (Kim, 2017) could have a considerable influence on stock returns. To accommodate for this a price relative, as proposed by Muller and Ward (2013), was utilised. Other studies attempted to remove the market fluctuation by the inclusion of dummy variables. This research report tried to evaluate the existence of The Weather Effect and its tradability, and not determine whether it excludes any macroeconomic fluctuation and seasonal effects.

This unit of analysis to address the theoretical case was different from what was performed by other weather effect studies (Goetzmann et al., 2015). Concerns were raised by the statistical community, as mentioned in Section 2.4, about the widespread misuse of the NHST and therefore this study provided an alternative method of proving the existence of The Weather Effect.

The traditional approach to test the business case; i.e. returns of portfolios, in quantitative analysis has been to report average monthly portfolio returns and after that to perform significance testing by the use of t-tests (Muller & Ward, 2013). For this to be valid, the assumption of a unimodal normal distribution has to be valid. Webb (2014) argued that

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monthly returns are non-normal and therefore this study will be utilising the related sample's Friedman ANOVA performed and Wilcoxon signed rank test to test the stated hypothesis. This method can produce dependable results from matched pairs of data from two populations (Kenkel, 1996); i.e. the benchmark and the weather portfolio, regardless of the underlying distribution.

Lockett et al. (2014) proposed that researchers should begin to de-institutionalise the practice of NHST in quantitative research, as this could lead to data mining in an attempt to provide statistically significant results, to get published. Therefore, graphical investigation of the various research questions was presented in this research report.

4.4 Data Gathering Process

Two sets of data were required for this thesis, the first was the stock prices and the second was the weather data for Johannesburg. The first set of secondary continuous data; i.e. stock process, was be obtained from Sharenet and Google Finance. The style engine that was utilised by Muller and Ward (2013) was populated by this adjusted financial data.

Unbundled subsidiaries were dealt with as separate entities' inclusion in the portfolios at the end of the holding period, as mentioned by Muller and Ward (2013). However, new companies had to have 60 months' worth of history before these could be included in a portfolio. The dividend pay-out data was obtained from INET, and as this would have been paid to the investor, this was added to the portfolio. For the benchmark, the J203T was utilised, which includes dividends. Share buy-backs and shares issued as compensation to managers were also excluded.

Share splits were also incorporated, where there was a movement of more than 40%, the price movement of the share was treated as zero. The database has been rigorously tested by Muller and Ward (2013) and was found to be sound and without discrepancies. Share splits or any consolidation which caused share price changes were backwardly adjusted in the database.

All shares listed on the ALSI in the time period were included in the dataset to control for survivorship bias. These stocks included delisted and newly listed companies. The

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methodology used accounts for the stocks entering and exiting the ALSI and the portfolios were based on shares on the JSE during at the time.

The second set of secondary date required was weather data, which was obtained from the SAWS. The research study's researcher acknowledged that weather data is not always available, as found by Kruger and Nxumalo (2017), and therefore listwise exclusion thereof was incorporated. No data homogenisation was performed, as proposed by the climatologists such as Kruger and Nxumalo (2017), which would account for the change in observation sites, observing practices and automation. The assumption made for this research study was that the data provided was sufficiently accurate as 15-day moving average day weather factors were utilised for the influence of mood on stock returns. This was a longitudinal study and therefore the need to compare the autocorrelation of the data, if present, was not part of the research.

4.5 Data processing and analysis

The style engine, as created by Muller and Ward (2013), was utilised for calculations to rebalance the all-weather portfolios. A weather function was created in Microsoft Excel™ to create the weather database as described in Section 4.5.1, whereafter this data was used to develop five weather portfolios, as described in Section 4.5.3. Microsoft Excel™ was used to perform the final processing and visualisation of the data. IBM SPSS was used for the statistical analysis.

Daily share prices have been found to be autocorrelated (Agiray, 1989), and therefore the previous day's share price might have influenced the next day's share price. This research study attempted to evaluate the change in weather factors and the correspondent change in stock prices. Therefore this study did not see it as advisable to use daily returns as a measure of the creation of weather betas, as indicated in Section 4.5.2.

Furthermore, utilising monthly data would remove the autocorrelation as it attempted to evaluate a longer history of the stocks, creating betas for a period of five years. Using shorter periods might be influenced by significant economic fluctuations such as market crashes of monthly effects. Calculations were performed at the end of each month, as well as the rebalancing of the portfolios, according to the methodology provided by Muller and Ward (2013).

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4.5.1 Weather Database

The weather data obtained from the SAWS was stored in a database. The average 15-daily average moving weather factor was calculated at the end of each month with a Visual Basic function from the weather database. This was in line with Yoon and Kang (2009) and Kang et al. (2010) who utilised a 21- and 31-day moving averages, however, 15 days were chosen as this was an optimised value for the JSE.

This research study did not utilise the deseasonalised weather as applied by Yoon and Kang (2009) because the researcher attempted to employ the absolute weather factors to establish investment style based on weather factors. The basis of The Weather Effect, the lack of serotonin in the event of cloud cover, is not a factor of being deseasonalised but rather being an absolute value. Young (Young, 2007, p. 395) found a direct correlation "serotonin synthesis and the hours of sunlight on the day the measurements were made, independent of season" (p. 395).

The second reason for utilisation of deseasonalised weather factors was posited by Cortés et al. (2016) and is explained as the removal of the intra-year economic cycles. The research report required the investigation of the performance of the weather portfolio during intra-year economic periods. Without this information, the study of the suitability as an investment style becomes superfluous.

Furthermore, various studies separate SAD and The Weather Effect. This research study assumed these two phenomena as the same, as both are based on medical evidence of changed behaviour leading to behavioural finance. Previous studies also found little correlation between mood-driven variation in day-to-day trading behaviour (Kaustia & Rantapuska, 2016). This research report, therefore, expanded on this premise and intended to extend the research into unchartered waters.

Each stock exchange is idiosyncratic and should, therefore, be treated differently. The moving average days of 15 was taken as this was the optimum of the average in the market value. A portfolio for each weather factor was created, whereby the portfolio was either in or out of the ALSI, depending on the moving average of the weather factor. If the moving average of the weather factor were within the range specified, such as between 20 and 28ºC for maximum temperature, then the portfolio would be in the market. The moving average days were varied until the optimum days were obtained. Results of the findings can be found in Chapter 5.

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The simple point moving average of the six weather factors were calculated

$$MA(W_t) = \frac{1}{15}(W_{t-21} + W_{t-20} \dots . + W_{t-1} + W_t) \qquad \text{Equation (3)}$$

Where W_t is the daily weather factor value at day t. The weather factors include the absolute barometric air pressure, the maximum temperature recorded for the day, the minimum temperature recorded for the day, the absolute rain of the day, the maximum wind speed and the cloud cover in octaves as recorded at 08:00. This is a slight variation on the simple centred moving average utilised in the literature (Yoon & Kang, 2009). Without knowing what the future weather effect would be, the validity of this assumption could prove difficult, therefore the backwards-looking model used in this research report.

4.5.2 Creating Weather Betas

The purpose of weather betas was to identify the correlation between stock price change and change in weather. This is different from studies from authors such as Schmittmann et al. (2015) who utilised a binary approach, using the median of the weather factor as the cut-off for the binary weather variables. Therefore, a value would either be positive or negative. Utilising this binary value would exclude any prevalent heteroscedasticity.

The first step was to create the difference in simple moving average weather factor values and stock price return. The difference of weather factor was taken as a mathematical difference while the monthly stock return day t (R_t) was calculated using natural logarithm

$$\mathrm{R_t} = ln\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}} \qquad \text{Equation (4)}$$

Where P_t is the price of the individual stock on day t and P_{t-1} is the price of the stock at the previous time period.

Data of 60 months were used to create weather betas, utilising end-of-the-month stock price data and weather data. These were calculated chronologically, prior to utilisation in

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the model to ensure that the betas were created for out-of-sample testing. The weather betas where then generated using Microsoft Excel™, expanding on equation (2)

$$R_t = \alpha_t + \beta_{p,t}Press_t + \beta_{max,t}MaxT_t + \beta_{min,t}MinT_t + \beta_{r,t}Rain_t + \beta_{w,t}Wind_t + \beta_{c,t}SKC_t + \varepsilon_t \quad \text{Equation (5)}$$

Where *Press* is the pressure, *MaxT* is the maximum temperature, *MinT* is the minimum temperature, *Rain* is the daily rain, *Wind* is the wind speed, and *SKC* is the cloud cover. The *β* is the beta for each individual weather factor with a subscript for the weather factors mentioned above. The subscript *t* refers to the time period.

In the model from Goetzmann et al. (2015) the month of January and Mondays has been omitted as he wished to control for seasonal anomalies. These were included in the research report as this anomaly were to be tracked on, as discussed in Section 4.5.1.

4.5.3 Creating portfolios

The one-month predicted returns were generated for each stock on the ALSI. The weather betas of the individual stocks and multiplying them with the expected difference in weather factor was based on the mean over the last ten years. The utilisation of the portfolios was taken out of sample. The stock forecast price of three months was expressed by the autoregressive forecasting model of the first order (Kenkel, 1996),

$$P_{t+1} = P_t + \alpha_t + \beta_{p,t}\overline{Press} + \beta_{max,t}\overline{MaxT} + \beta_{min,t}\overline{MinT} + \beta_{r,t}\overline{Rain} + \beta_{w,t}\overline{Wind} + \beta_{c,t}\overline{SKC} \quad \text{Equation (6)}$$

These stock returns were ranked from highest to lowest expected returns or forecast value and after that added into one of five bins. These five bins consisted of 32 shares that became the equally weighted portfolios. The forecast value was called Forecast1 through to Forecast5, while the actual returns of each portfolio were called Weather1 though to Weather5.

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A secondary portfolio was created; WeatherOptBest and WeatherOptWorst, which is the optimised portfolios. The former was constructed of the stocks ranked 11 through to 30, while the latter were stocks ranked 150 through to 160. In both cases, the stocks in the portfolio were equally weighted.

The projected average weather change, based on the previous ten years of weather measurements were inserted into the model and stocks expected to perform well as a result of the predictive model were purchased during the rebalancing phase.

4.5.4 Analysis the data

The weather portfolio return was graphically analysed to reveal differences in returns using a graphical time series approach to, as utilised by Muller and Ward (2013). The various portfolios were presented on a scatter graph which indicated the relationship of return over time for the multiple quintiles. The market capitalisation weighted ALSI total return index (J203T) was utilised as the benchmark and plotted on the same graph.

A price-relative between the highest ranked portfolio, and the J203T and the highest-lowest expected portfolios were plotted. This provided the opportunity to evaluate performance over time.

The compound annual growth rate (CAGR) was calculated by using

$$\mathrm{CAGR} = \frac{\mathrm{P_i}^{\frac{1}{n}}}{\mathrm{P_0}} - 1 \qquad \text{Equation (7)}$$

Where P_i is the value of the portfolio at the end of the timeframe, P_0 is the value of the portfolio at the start of the timescale, and n is the period of investment in years.

The monthly stock returns has non-parametric distributions as found by Webb (2014) and therefore required a non-parametric statistical test. This test was only used as a secondary measuring tool, as the primary measuring tool was the cumulative returns as indicated by the CAGR of each portfolio.

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The use of cumulative returns was found to be superior testing techniques by Muller and Ward (2013). This was in line with findings of the literature study, as indicated in Section 2.4, which raises concerns with the use of statistical methods when analysing data. The work done by Wasserstein and Lazar (2016), as shown in Section 2.4, raised concerns about the widespread misuse of null hypothesis significance testing (NHST). Statistical significance as the sole criteria of the importance of quantitative research findings creates the fear that data mining would be used.

4.6 Limitations

The limitations identified on the methodology presented in this Chapter are shown in this section. The transaction cost of quarterly rebalancing was ignored. The share prices were only taken as end-of-day values. Hence any intraday trading fluctuations were not taken into account. Pizzutilo and Roncone (2016) stated that the morning weather would have influences across the entire day.

The study was only performed on the JSE, as this study had been conducted on other financial markets by others. These financial markets led to different results, and various authors found a varying degree of influences of The Weather Effect.

It is possible that the relationship during the period of time was more or less severe as a result of changes in technology, changes in human behaviour, and changes in geopolitics which could have severe implications for future returns. Decreasing influence of The Weather Effect has been found by Smith and Zurhellen (2015).

The question of highly liquid shares was raised. Illiquid stocks might have performed better than their more traded counterparts, however, this model which was tested assumed that trading took place immediately. Therefore, trading in a volatile market when shares are on the retreat outside the simulation might be different from what the model predicts.

It was required that the stock was on the JSE for longer than five years (60 months) before it entered the portfolio. This could influence results as only seasoned companies were included. Schneider (2014) found technology stocks being most susceptible to The Weather Effect and these would typically be excluded due to the nature of these companies.

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The various stock had different R-squared values. The ranking of the shares did not take this into account but produced expected returns, irrespective of the correlation with the weather factors. This suggested high yield, and low R-squared stocks could have had a substantial impact on the portfolios.

The expected returns were based on the last 10 years' average weather factors. Therefore, it was not based on actual weather, but on the average over the past. The concern with this methodology is the investigation of seasonal traits instead of the real weather.

Some of the investment styles analysed by Novy-Marx (2014) could be seen as riskier and therefore would supply superior returns during specific periods. However, work performed by Cohn et al. (2015) suggested that exogenous factors, which had not been investigated in this study, could influence countercyclical risk aversion and therefore skew the results. The researcher attempted to address this concern by running the time period past the stock market crash in 2008.

To create expected future returns, an OLS on a specific stock was utilised. The OLS assumes that there are no heteroscedasticity or autocorrelation (Kenkel, 1996). However, this assumption is crude.

4.7 Conclusion

The research methodology as proposed in this Chapter finds its origins in work performed by Muller and Ward (2013) and expands thereon in an attempt to investigate The Weather Effect on the JSE. The results of the quantitative analysis can be found in Chapter 5.

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CHAPTER 5: RESULTS

The results presented in this Chapter addresses the research questions as introduced in Chapter 3 during the period from 31 December 2001 until 31 March 2017. Section 5.1 indicates where the optimised moving average of 15-days was obtained. The forecasted, otherwise known as the weather expected returns and actual returns as presented in Section 5.2 addresses the first research question, the presence of The Weather Effect on the JSE. The gains of the five different quintiles of the portfolios and the optimised portfolios are presented in Section 5.4, which addresses the second research question, whether The Weather Effect can be used to outperform the market.

Two different analysis has been used to evaluate the research questions; NHST and graphical time series. The results of the portfolio performance are compared visually, in the graphical time series method proposed by Muller and Ward (2013), and statistically as proposed by Webb (2014). The portfolio performance is compared to the benchmark, the ALSI total return index (J203). Please note that a value of one is given to each portfolio at the start of the period for ease of comparison. The two-tailed statistical test, as was required by the hypothesis in Chapter 3, was performed by the non-parametric tests. The z-statistic for each pair was calculated by SPSS at the statistical significance 5% level.

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5.1 Optimisation of Moving Average Days

The optimised 15 days were obtained from investigating the maximum influence each weather factor identified in this report, has on The Weather Effect. This was done by examining the maximum returns provided by a binary portfolio, either being in or out of the ALSI, as explained in Section 4.5.1. This was done for the time period between 31 July 1984 and 31 March 2017. The detailed breakdown of each individual weather factor moving average days is displayed in Table 1.

Table 1: Moving Average Days

Weather Factor	Moving Average Days
Cloud Cover	15 days
Daily Rain	10 Days
Minimum Temperature	29 Days
Maximum Temperature	22 Days
Pressure	25 Days
Wind Speed	13 Days

5.2 Research Question One

Research question one as presented in Chapter 3 addressed whether The Weather Effect can predict future all-weather portfolio returns. The Wilcoxon sign rank test indicates that the null could not be rejected. This section displays the weather expected returns of the created portfolios and compares these with the realised returns.

The graphical times series forecast monthly returns of the five different portfolios, called Forecast1 through to Forecast5, are presented in Figure 1. The x-axis is the time period, from 31 December 2001 until 31st of March 2017 while the y-axis is the weather expected return or the forecast value as a percentage change from previous value. The first quintile, called Forecast1, consists of the highest weather expected return stocks and provides a mean return of 4.26% per month. Quintile five, called Forecast5, comprises of the lowest weather expected return stocks and provides a mean return of -2.34% per month.

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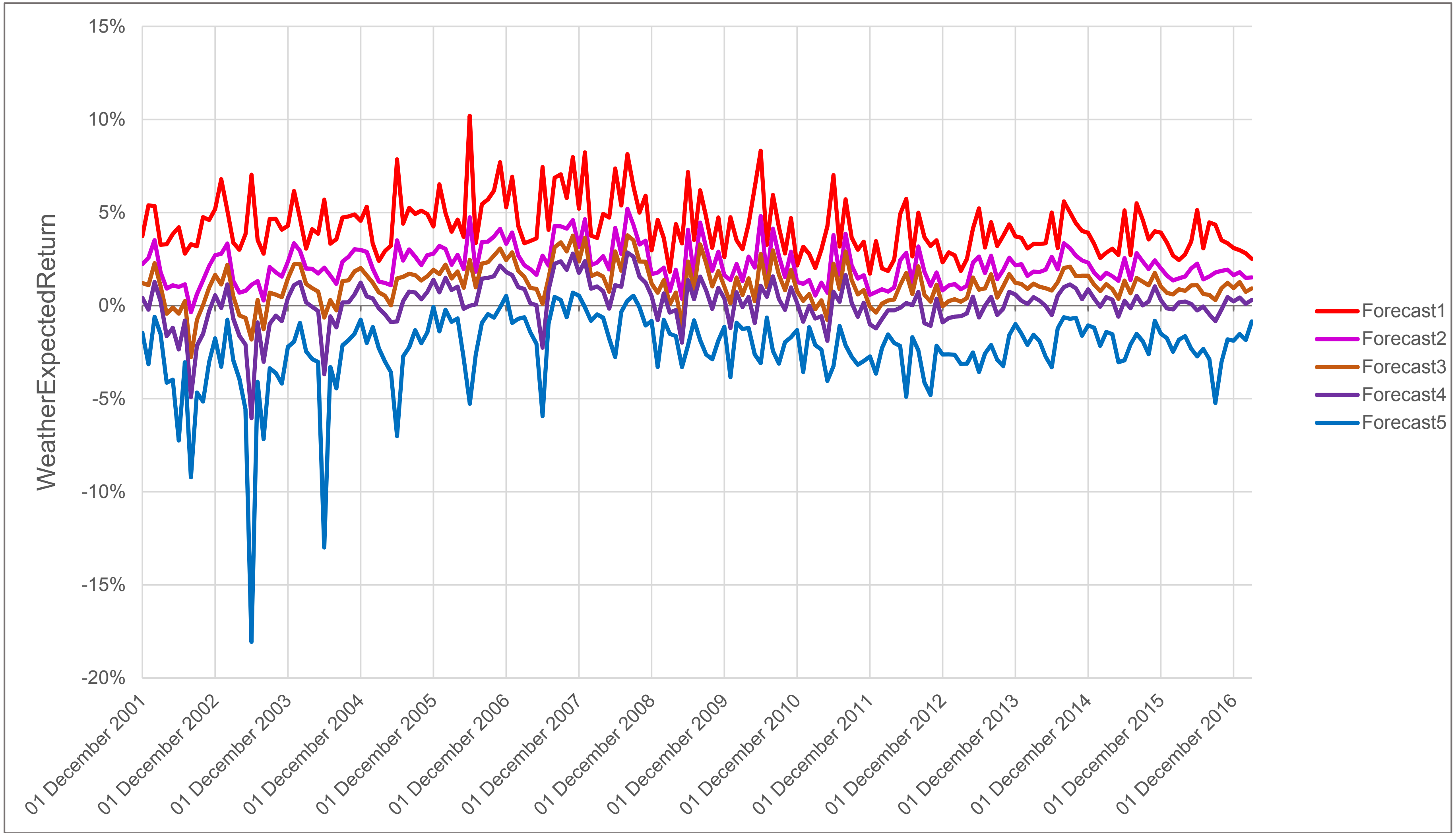
Figure 1: Weather Expected Return



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The descriptive statistics of these forecasted portfolio returns and the mean returns can be found in Table 2. The first column identifies the portfolio, the second indicates the mean and the last column indicates the standard deviation.

Table 2: Forecasted Returns

Weather Portfolio	**Mean Returns**	**Standard Deviation**
Forecast1	4.26%	0.11%
Forecast2	2.18%	0.07%
Forecast3	1.16%	0.07%
Forecast4	0.11%	0.08%
Forecast5	-2.34%	0.15%

The descriptive statistics of the materialised monthly returns of the various portfolios are displayed in Table 3. The first column indicates the portfolio; the second shows the mean and the last column shows the standard deviation.

Table 3: Weather Returns

Weather Portfolio	**Mean Returns**	**Standard Deviation**
Weather1	2.00%	0.33%
Weather2	1.57%	0.29%
Weather3	1.57%	0.29%
Weather4	1.58%	0.30%
Weather5	2.08%	0.52%

The Wilcoxon signed rank test was used to evaluate the forecast and weather portfolios, and it was found that null could be rejected for the alternative for Forecast1, which is the research question. Further analysis was performed, and it was found that the null could not be rejected for Forecast2 and Forecast3. The null could be rejected in favour of the alternative hypothesis in Forecast4 and Forecast5. The z-statistic and Wilcoxon signed rank *p*-value are displayed in Table 4. The number of negative ranks represents the instances where the Forecast portfolio was more substantial than the Weather portfolio.

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Table 4: Hypothesis One Test Results

Weather Factor	**Z-Statistic**	**Wilcoxon Signed Rank *p*-value**	**Sample Size**	**No of negative ranks**
Forecast1 and Weather1	-5.801	0.000*	184	57
Forecast2 and Weather2	-1.183	0.237	184	85
Forecast3 and Weather3	-1.498	0.134	184	98
Forecast4 and Weather4	-4.710	0.000*	184	123
Forecast5 and Weather5	-8.617	0.000*	184	145

Note: * indicates statistical significance at the 5% level

The graphical time series of the weather expected portfolio under investigation for the research question can be found in Figure 2. The clustered column graph shows the Forecast1 portfolio, the weather expected returns portfolio, in blue and the Weather1 portfolio, the realised returns portfolio, in orange.

From this section, the first research question was addressed, and it was found that null could be rejected in favour of the alternative hypothesis.

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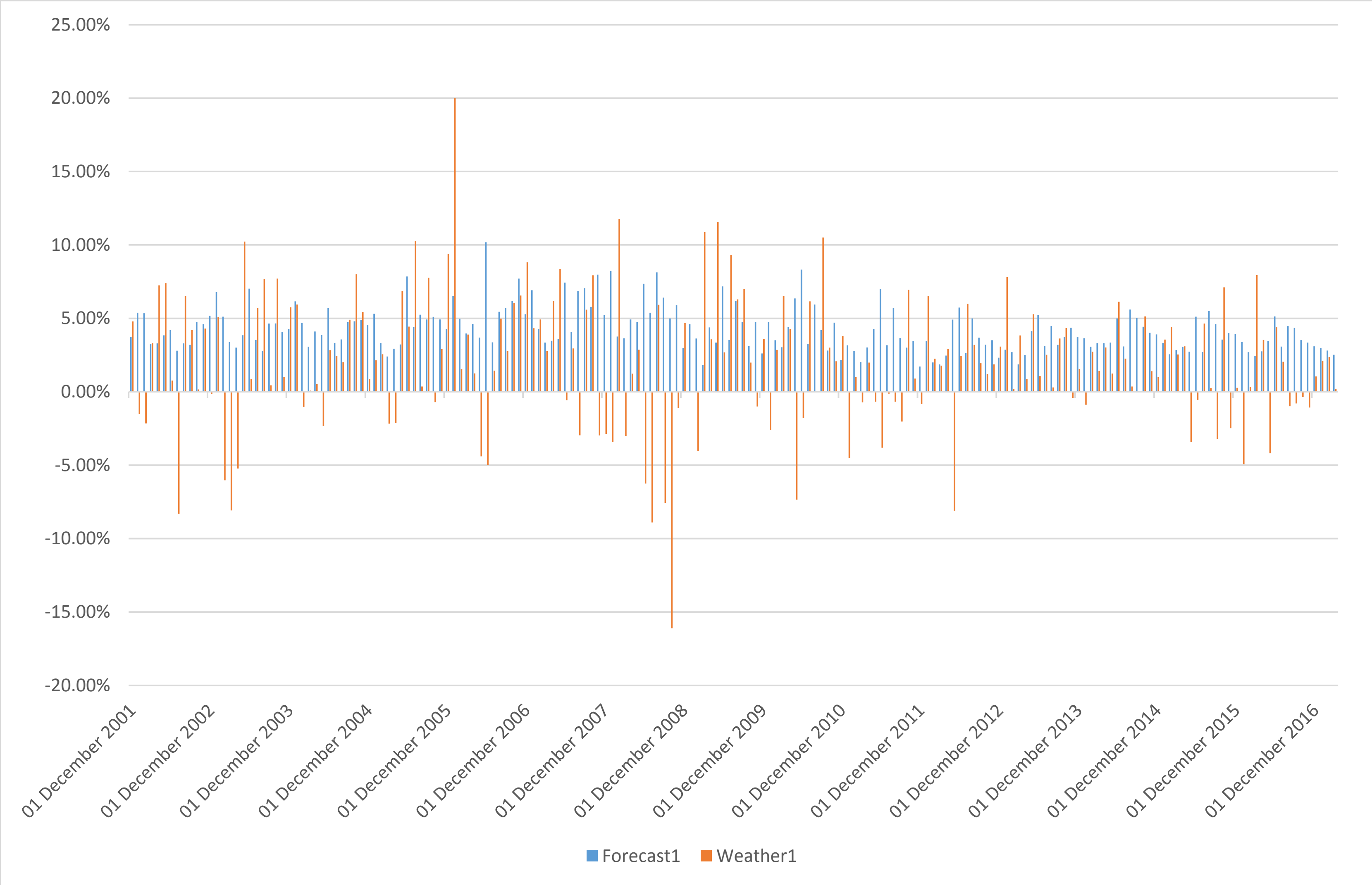
Figure 2: Graphical Time Series of Forecast1



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5.3 Weather Betas

The model proposed consists of six betas, one for each weather factor, as indicated in Equation 5. Each weather beta was calculated, as well as the number of occasions the associated z-stat at 95% significance level was achieved. The cumulative significant results for each weather factor was taken as a percentage and is shown in Table 5. From this table, it is evident that cloud cover provides the best explanation within the model, with a value of 6.95%. The absolute barometric air pressure provides the lowest level of significance with only 4.54% of the times.

Table 5: Weather Beta Statistical Significance

Weather Factor	**Statistical significant percentages**
Cloud Cover	6.95%
Daily Rain	5.32%
Minimum Temperature	4.67%
Maximum Temperature	6.14%
Pressure	4.54%
Wind Speed	5.48%

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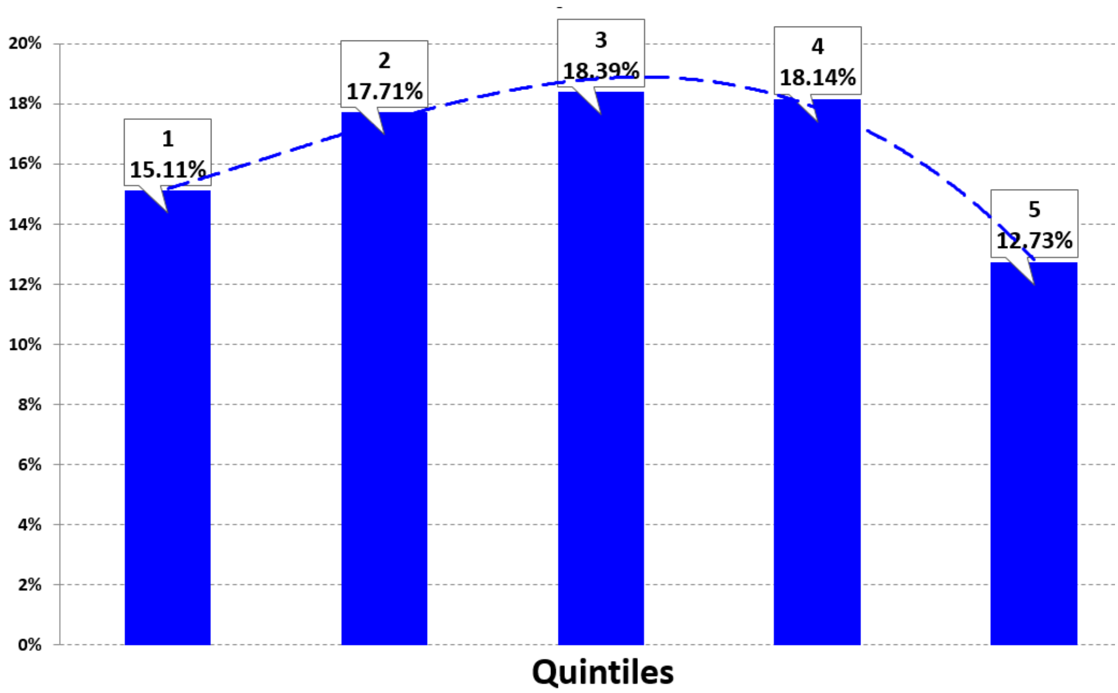
5.4 Research Question Two

The results of the question whether The Weather Effect can be utilised to outperform the market is displayed in this section. The various analysis, graphical and statistical, is presented in this section for the quintile performance to address the research question. Review of the optimised portfolio has also been included as a hedging strategy.

5.4.1 Quintile Performance

The realised returns of the five different quintiles are presented in Weather1 to Weather5, which are the five different portfolios created. The realised CAGR for each weather portfolio was calculated and is displayed in Figure 3. These returns should be compared to the benchmark, the J203T, which produced returns of 14.5% over the same period. Quintile 1 provided slightly better average returns of 0.6% than the benchmark, but only since the start of 2015. From the research study's model, it was expected that it would provide a superior return of 4.39% as indicated in Table 3. Quintile 2 provided a return of 17.71%, quintile 3 provided the best return of 18.39%, and quintile 4 provided returns of 18.14% while quintile 5 provided returns of only 12.73%.

Figure 3: Weather quintile performance



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The null was rejected as the *p*-value of the related samples Frieman's two-way ANOVA of variance by ranks of the five weather portfolios and the J203T is 0.045. The results of the post hoc analysis as performed by the Wilcoxon signed rank test is indicated Table 6. The null could not be rejected for Weather3 and Weather4. The number of positive ranks shows the incidents where the weather portfolio outperforms the benchmark, the J203T.

Table 6: Hypothesis Two Test Results

Weather Factor	**Z-Statistic**	**Wilcoxon Signed Rank *p*-value**	**Sample Size**	**No of positive ranks**
Weather1 and J203T	-3.130	0.002*	184	115
Weather2 and J203T	-2.447	0.014*	184	111
Weather3 and J203T	-1.762	0.078	184	99
Weather4 and J203T	-1.754	0.079	184	99
Weather5 and J203T	-1.996	0.046*	184	103
Weather1 and Weather5	-0.921	0.357	184	89

Note: * indicates statistical significance at the 5% level

The logarithmic graphical time series results are displayed in Figure 4. The weather portfolios are shown as Weather1 to Weather5 while the price relatives as Q1 versus Q5 and Q versus J203T. Q1, short for quintile one, represents Weather1 while Q5, abbreviation for quintile five, represents Weather5. A trend line of R-squared 0.67 has been added for evaluation of the Q1 versus Q5's relative performance.

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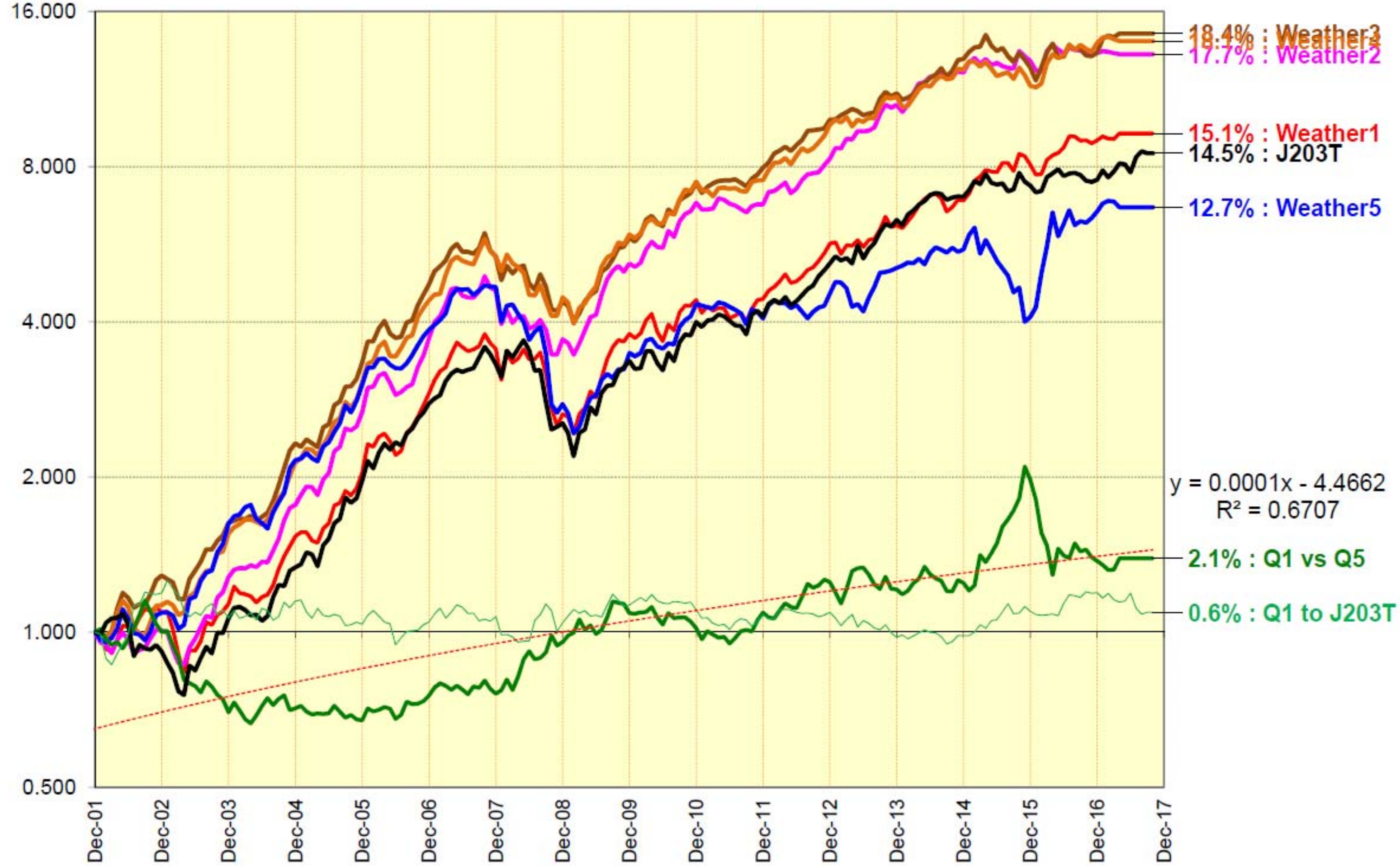
Figure 4: Weather Portfolio



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5.4.2 Optimised Portfolio Performance

The utilisation of The Weather Effect as a hedge strategy (Dong & Tremblay, 2011; Schneider, 2014) requires the inclusion of the optimised portfolios analysis. WeatherOptBest is an optimised weather portfolio. WeatherOptWorst is an optimised portfolio of the worst performing stocks.

The statistical analysis using the related sample's Friedman test leads to the null being rejected in favour for the alternative, as the *p*-value found in this test was 0.11. The post hoc Wilcoxon signed rank test results are displayed in Table 7.

Table 7: Test results of Optimised Portfolio

Weather Factor	**Z-Statistic**	**Wilcoxon Signed Rank *p*-value**	**Sample Size**	**No of positive ranks**
WeatherOptBest and J203T	-2.388	0.017*	184	109
WeatherOptBest and WeatherOptWorst	-1.549	0.121	184	107

Note: * indicates statistical significance at the 5% level

The logarithmic graphical time series results are displayed in Figure 5. The second figure displays the optimised weather portfolios, as described in Section 4.5.3. OptBest versus Worst is the price relative between the best and worst predictive portfolios. The price relative with R-squared of 0.76 was included.

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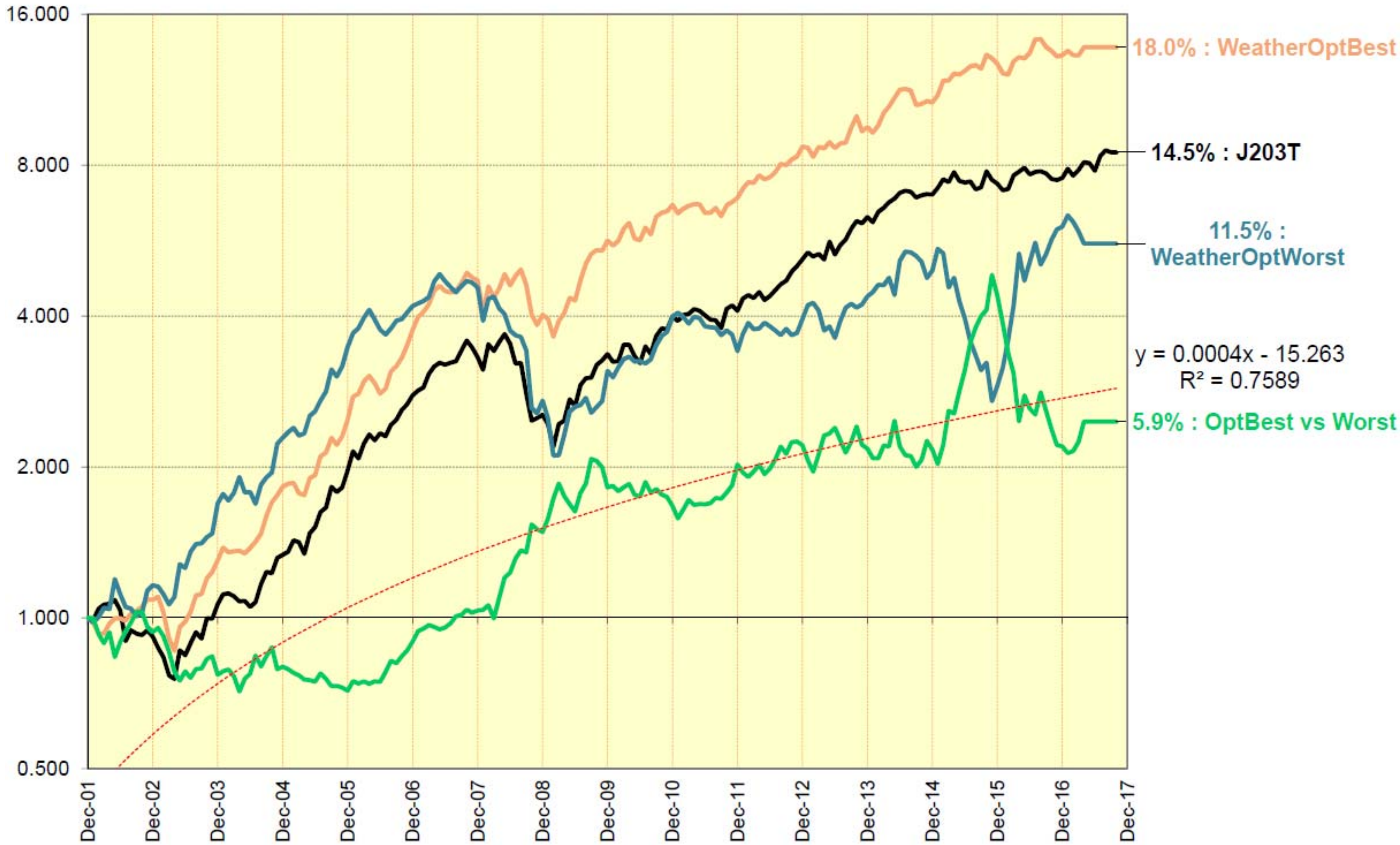
Figure 5: Optimised Weather Portfolio



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5.4.3 Conclusion

From this section, it was concluded that the null was rejected by use of the Friedman non-parametric test. The optimised weather portfolios were only created as further investigation into utilisation of The Weather Effect, but similar results were obtained.

5.5 Validity of Data

The assumption was made that the returns were non-normal distributed, as recommended by Webb (2014). This was confirmed by the Shapiro-Wilk test for the monthly returns with all portfolios, except Weather3 and Weather4, being non-normally distributed as their *p*-value was less than 0.05 (see Table 8 for the test results).

Table 8: Test for Normality Shapiro-Wilk

Weather Factor	**Statistic**	**Sample Size**	***p*-value**
Weather1	0.980	184	0.009*
Weather2	0.981	184	0.014*
Weather3	0.995	184	0.766
Weather4	0.986	184	0.073
Weather5	0.716	184	0.000*
WeatherOptBest	0.980	184	0.009*
WeatherOptWorst	0.971	184	0.001*
Forecast1	0.938	184	0.000*
Forecast2	0.971	184	0.001*
Forecast3	0.982	184	0.016*
Forecast4	0.918	184	0.000*
Forecast5	0.742	184	0.000*
J203T	0.966	184	0.000*

Note: * indicates statistical significance at the 5% level

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CHAPTER 6: DISCUSSION OF RESULTS

From behavioural finance literature, it was evident that there exists a weather-induced mood variation which influences the valuation of assets (Goetzmann et al., 2015; Hirshleifer, 2015; Schmittmann et al., 2015; Smith & Zurhellen, 2015). The Weather Effect was found on the JSE by various authors, as discussed in Section 2.5. However, the researcher shared concerns that proof of The Weather Effect was a result of data mining (Kim, 2017; Pizzutilo & Roncone, 2016) as the NHST is incorrectly used (Wasserstein & Lazar, 2016).

From the results as presented in Chapter 5, the difference in performance of the proposed portfolios was found, but the argument is made that it is the result of data mining and not as a result of The Weather Effect, which is similar to the findings of Kim (2017). The benchmark could also not be beaten with consistency, answering the second research question. This research report concurs with the results of Muller and Ward (2013) in that a superior method for evaluating returns, namely graphical time series, should be utilised.

6.1 Optimisation of Moving Average Days

The optimised moving average days of 15-days were found for The Weather Effect on the JSE as indicated in Section 5.1. This is in line with, but slightly lower than results yielded by Yoon and Kang (2009) and Kang et al. (2010). The various weather effects had different optimised days as evidenced in Table 5. This is the first time weather factor varying optimised moving average value has been identified, as far as the researcher could find in literature. Past studies have only focussed on individual elements, always assuming there is one constant value influencing moving average day for all elements.

The optimised findings concur with the momentum of weather as first raised by Schmittman et al. (2015). These authors argued that The Weather Effect is stronger if good or bad weather is prevalent over several days. From a medical perspective, this is as a result of cumulative serotonin levels increased by means of sunlight (Van Der Rhee et al., 2016; Young, 2007) or the varying tryptophan production as a result of barometric air pressure (Radua et al., 2010). It has also been found that other weather factors are influenced as a result of thermoregulatory needs of individuals (Parker & Tavassoli, 2000).

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The momentum in weather puts into question studies which have attempted to evaluate stock price changes based upon hourly weather. Authors who utilised the method of intraday trading influenced by the weather were Pizzutilo and Roncone (2016) and Lu and Chou (2012), but their findings are that The Weather Effect is statistically insignificant. Chang et al. (2006) utilised the Ljung-Box Q statistics to indicate that the returns are serially correlated and with time lags of 5 and ten periods, significant dependencies exist in the stock returns and weather factors.

The first author who raised concerns about the existence of The Weather Effect, Krämer and Runde (1997), expressed concerns about how the null is phrased would influence the results. This research report expanded upon in this matter and argues that the methodology utilised, such as intraday trading, would affect the findings. This finding validates the assumption of employing moving average daily weather factor values instead of daily values.

6.2 Research Question One

Research question one attempted to address the ability of the weather factors to predict future returns. The results demonstrated that there were indications that the null was rejected and therefore The Weather Effect could not be utilised to predict future returns. This section is divided into the findings of the research question, and a section on conclusions which leads into future work.

Five portfolios were created by this research report, representing predicted returns based on The Weather Effect. These portfolios address the concerns raised by Pizzutilo and Roncone (2016), who argued that for The Weather Effect to be present, it should be discernible not only as found on index level. Pizzutilo and Roncone (2016) explained that the broad market and less exposed to behavioural inefficiencies.

A concern to be address is the validity of the research question. Concerns of data mining has been raised on the existence of The Weather Effect across the globe (Gerlach, 2007; Jacobsen & Marquering, 2008; Kim, 2017; Krämer & Runde, 1997; Loughran & Schultz, 2004; Pizzutilo & Roncone, 2016; Trombley, 1997). This concern is influenced by the way the research question is phrased in an attempt to provide statistically significant results (Wasserstein & Lazar, 2016). In the method the five different portfolios have been created, Weather2, Weather3 and Weather4 are more inclined to predict returns in line

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with the general market and therefore have statistically significant results. Weather1 and Weather5 anticipate unusual weather expected returns. The top return predicted portfolio would also be utilised in the business question, as seen in Section 6.4.

6.2.1 The Findings

In the literature The Weather Effect was found by Hirshleifer and Shumway (2003), Kamstra, Kramer and Levi (2003) and Apergis and Gupta (2017) to be present on the JSE. Hirshleifer and Shumway (2003) found a positive correlation between cloud cover and stock returns on the JSE. This research report contradicts these studies but agrees with the study of Kim (2017) that by only utilising the NHST could lead to spurious correlation. Other reviews also agree with is that of Jacobsen and Marquering (2008) who argued that SAD not be the only influencing factor predicting the stock returns. Jacobsen and Marquering (2008) say that it could be as a result of the Sell-in-May effect. Inference can be made that Apergis and Gupta's (2017) study would have the same problems with sample size, as raised by Kim (2017), with the study running from 1973 until 2015. This research report finds that the methodology utilised by the researcher could influence the results. Please see Section 6.1.

The Wilcoxon signed rank test indicated in Section 5.2 that the null was rejected. The null was rejected in favour of the alternative for Forecast1, Forecast4 and Forecast5, as indicated in Table 4. This finding suggests that the differences are not statistically significant. The null could not be rejected for Forecast2 and Forecast3. This validates the assumption of utilising only Weather1 as other portfolios would provide data mined results.

An increasing level of negative ranks was found in the weather portfolios as indicated in Table 4. This change in rank suggested that the all-weather portfolio provides more substantial returns than forecasted on more occasions as the rank increases. The mean returns of the forecasted mean returns decrease with increase in the portfolio number as indicated in Table 2, but the realised returns do not. The realised returns can be found in Table 3. The portfolios are predicting bad results, but the actual portfolios perform better than expected.

The portfolio with the largest concern is that of Forecast5, which predicted a mean return of -2.34%, but delivered a mean return of 2.08%. Furthermore, the Wilcoxon signed rank

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test indicates a *p*-value of 0.000 and z-statistic of -8.617. This suggested that all-weather portfolios, in particular, Weather5, was incapable of predicting future returns.

6.2.2 Further Investigation

Figure 1 demonstrates the expected performance against the actual performance in of the portfolios addressing the research question. From this figure, the following is concluded:

- The forecast predicts a vast majority of positive returns, while this is not present in the real performance.
- The predicted values are far from accurate, which is indicated in the means and standard deviation as per Table 2 and Table 3.
- There is a form of seasonality included, which is not evident from the actual returns. Although the null hypothesis could not be rejected, this research report argues that the weather is not a reliable method for predicting returns on the JSE.

Trombley (1997) argued that the little correlation on the NYSE only appear during certain months of the year. This raised the concerns that The Weather Effect is, in fact, a seasonal anomaly, as is the Sell-in-May effect. The investigation into the graphical time series analysis of Figure 1 leads to forecasted seasonalities. Higher returns are forecasted in June which gradually decrease over the next few months. From this, it can be concluded that the model predicts seasonal returns. The cloud cover is, in fact, positively correlated with returns Hirshleifer and Shumway (Hirshleifer & Shumway, 2003), which would lead to decreasing cloud cover towards the end of the rainy season that should yield increased returns. These increased returns although not exactly in line with the Sell-in-May effect, have a striking resemblance to this stock market anomaly. The positive correlation between cloud cover (Hirshleifer & Shumway, 2003) and the SAD effect (Kamstra et al., 2003) could indicate seasonal anomalies.

The highest divergence between Forecast1 and Forecast5 returns were evident in June, see Figure 1. This also indicated seasonality in the predictions. This seasonal prediction decays over time, from a maximum of 33% in June 2003 to 13% in June 2016. This was in line with findings of Smith and Zurhellen (2015). As the market became more efficient, the influence of behavioural finance reduced, eventually becoming insignificant as presented in the model prediction. Another possible explanation was provided in the form

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of market learning, as proposed by Adam, Marcet and Nicolini (2016) who argued that learning about price behaviour could lead to understanding stock price volatility.

Volatility was excluded in the model, which questions the results. Higher volatility, typically associated with market crashes, could influence the projections. The influence would be in the creating the weather betas, as discussed in Section 4.5.2. Furthermore, the standard deviations of the forecasted values are lower than the realised returns, as indicated in Table 2 and Table 3. The model is found to lack in predicting volatility, which could have been better anticipated using the GARCH model (Agiray, 1989). The GARCH model is utilised by other authors (Chang et al., 2006; Floros, 2011; Kang et al., 2010), but the methodology employed in this research report does not cater for autocorrelation in returns as monthly data is used.

6.2.3 Conclusion

It was concluded that The Weather Effect could not be utilised to predict future returns on the JSE. From the results displayed in Section 5.2, this research report proved that there was statistical significance in individual portfolios, but this can be ascribed to data mining as emphasised in the study performed by Kim (2017) as the NHST was utilised. The findings of this report are in line with that of Kaustia, and Rantapuska (2016, p. 24) who found the “overall magnitude of the mood effect on trading is weak at best”. Continuing from the recommendations of Wassertein and Lazar (2016), NHST finding was not used as the sole criteria in importance findings, but rather an alternative approach in phrasing the null which results in a lower possibility of significance. The graphical time series results finding is that The Weather Effect is not predictable. Although the idiosyncratic behaviour of the Johannesburg investors on the JSE was not overlooked, the results from this study cannot be superimposed, but instead, could be utilised on other stock exchanges.

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6.3 Weather Betas

The investigation into which weather factor has the highest influence on the stock exchange was never part of the original scope, but some interesting results were found. From the number of statistical significance instances of Weather Betas, as indicated in Section 5.3, it can be concluded that cloud cover has the most significant chance of providing an accurate future prediction, as it has the highest level of statistical significant instances.

The low level of significance of each individual weather beta, as indicated in Table 5 is concerning when a significant result is required. These low levels of consequence would lead to a virtual impossibility to accurately predict the future returns. From the literature review, Hirshleifer and Shumway (2003) found that their t-statistic for Johannesburg cloud cover is 0.28. The t-stat is not in the same estimated rankings for the results that were obtained in this report. This suggests that the betas have little predictive power over the future returns, questioning the correlation between the weather and stock returns.

This finding is in line with results from Hirshleifer and Shumway (2003) who found cloud cover to have the highest influence on the New York Stock Exchange, and therefore extended its analysis onto the JSE. It has been argued that each stock exchange is idiosyncratic (Pizzutilo & Roncone, 2016), which would be true, but similarities between stock exchanges do exist.

The results found in Section 5.3 will be skewed as the optimum moving average days were taken as 15. The 15-days is the optimum value of cloud cover and is closer to daily rain and wind speed than it is to the amount of the maximum and minimum temperature and pressure.

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6.4 Research Question Two

From the literature study, as mentioned in Section 2.3.3, various authors found arbitrage opportunities created from The Weather Effect. This section expands on the significant results found in Section 5.4. The quintile performance expressed in Section 6.4.1 has been used to address the research question, but further analysis was performed in Section 6.4.2.

Schneider (2014) found economically significant results, but none were statistically significant. Therefore, even though research question one, as indicated in Section 6.2, was found not to be statistically significant, it does not exclude the possibility of finding an arbitrage opportunity in The Weather Effect.

6.4.1 Quintile Performance

Research question two addressed whether the weather portfolio created would outperform the benchmark. The null hypothesis was rejected indicating that the distributions are not the same. An investigation into the graphical time series results revealed that Weather1 only slightly outperforms the market with a 0.6% CAGR, as indicated in the price relative in Figure 4. Although the NHST resulted in significant findings, the graphical time series analysis suggests that The Weather Effect cannot be utilised to outperform the market.

The graphical time series analysis in Figure 4 raised concerns about the individual portfolio performance. If The Weather Effect could be successfully utilised, the ranking in performance should be in sequence; i.e. Weather1 with superior returns and Weather5 inferior returns. These weather portfolios should have a mean around the value of the JSE, but this was not the case. Weather2, 3 and 4 were by far the superior performing portfolios. A decreasing number of positive ranks, as provided in Table 6, was expected, to tie in with the NHST. However, this decreasing number of weather portfolio was not present, indicating that The Weather Effect cannot be successfully utilised to outperform the market.

The OLS of deseasonalised weather effects, as provided in the study of Lu and Chou (2012), utilises daily indices returns. The OLS model does not account for the autocorrelations as per the GARCH model which. The justification for employing the former is that the monthly returns in the weather portfolios are non-normally distributed,

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as the Shapiro-Wilk test confirms. Please refer to Section 5.5. The GARCH model is based upon autocorrelations which are data that is normally distributed.

The superior returns of Weather3 and Weather4, as seen in Figure 1, could be explained by work done by Novy-Marx (2014), who found that certain investment styles perform better during better weather. Some of these effects could have inadvertently been included in the portfolios, such as the size-effect. These other style inclusions could lead to tradable superior performance. It could be argued that the equally weighted structure of the weather portfolios could have influenced the results as the J203T is value weighted and therefore more portfolios perform better than the benchmark. In the graphical time series analysis of the model, four of the five weather portfolios outperformed the benchmark (J203T).

There was a sharp decrease in the performance of portfolio Weather5 in 2015. In 2016 there is a correction in this portfolio, but the all-weather style did not accommodate for correcting thereof. The correct implementation would be the inclusion of these recovering stocks in Weather1 and not Weather5. This indicated that investment style is not robust in accounting for macroeconomic factors.

It can be seen that Weather5 had only been on the decrease since the market crash of 2008, and never recovered thereafter. Investing in The Weather Effect before 2008 would have lead to economic losses. The recession during 2008 would also influence sentiment, as investor sentiment has a prominent effect during bad times (Garcia, 2013). It has been found that investor sentiment influences stock returns (Siganos et al., 2017). No investigation into investor sentiment was performed in this study.

An interesting phenomenon identified is the dip in the value of Weather5, indicating a yet undefined market phenomenon on the JSE literature. The fall in performance in 2015 and subsequent recovery could be attributed to the inclusion of resource stocks in this portfolio during this time. Lonmin Plc decreased 25% in March 2015, 19% in June 2015, 51% in July 2015 and a further 29% in August 2015. Kumba Iron Ore decreased 29% in March 2015 28% in May 17% in August, 13% in September and 24% in October. African Rainbow Minerals, Anglo American PLC and Lonmin Platinum returned in excess of 50% during the month of February 2016. During the same period, Kumba Iron Ore returned a great 108%.

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6.4.2 Optimised Portfolio Performance

The inclusion of optimised portfolios was included as the possibility exists to use The Weather Effect as a hedge strategy (Dong & Tremblay, 2011; Schneider, 2014). WeatherOptBest consisted of the ten worst forecasted stocks of Weather5, and therefore a correlation in performance was expected. WeatherOptWorst consisted of the shares in Weather1 and Weather2. No out of sample test was performed by this empirical optimised portfolios, which therefore limits the validity of the use of recommendations.

The WeatherOptBest outperformed WeatherOptWorst with a large margin, at a CAGR of 5.9%. Please see Figure 5. The trend line has a higher beta (0.0004) than that of Weather1 against Weather5 (0.0001) in Figure 4, indicating the highest continuous increase in performance. This is in contrast with findings from Yoon and Kang (2009) who found an decreasing level of influence. However, WeatherOptBest only performed better than WeatherOptWorst with 107 versus 77 of the times, as shown in Table 6. The return only increased from 2006 until 2017, before then there was a decrease in returns, as indicated by the price relative. These optimised portfolio values are very similar to the findings of Kamstra et al. (2003) who found annualised returns of the SAD influence on the JSE of 17.5% versus the JSE returns of 14.6%.

Comparing the two optimised portfolios, WeatherOptBest versus WeatherOptWorst, it was evident that from 2006 until the end of 2015 WeatherOptBest achieved superior returns. It performed better during the market crash of 2008 and also during the market anomaly in 2015.

De Prado (2015) argued that arbitrage phenomena which are created, such as The Weather Effect would be dampened and would eventually be removed. From the trend, it was evident that the little arbitrage opportunity between WeatherOptBest and WeatherOptWorst has only increased during the time period of the study. This could either be ascribed to the limited research on The Weather Effect performed on the JSE, or is otherwise an indication that the EMH has still not been reached and that the market has become less efficient since 2008. This could not be verified by any literature and was not part of the original investigation of this report and is therefore not included as a finding.

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6.4.3 Conclusion

With the realised weather returns on the increase and the variance in forecast value on the decrease, it could be argued that the model has become more accurate in predicting future returns. However, this cannot be concluded from this research report as there is the probability that volatility has played a role in the decrease of variance. As mentioned in Section 2.3.2, Adam et al. (2016) proposed that learning about stock price behaviour could lead to better understanding of volatility. Could it be that investors have learned and can better understand volatility during the period between 2001 and 2017?

The proposed hypothesis compared The Weather Effect with that of the market. The ALSI was used as a benchmark. If one would consider it against other investment styles on the JSE, different investment styles perform in a far more superior manner. In the study by Muller and Ward (2013, p. 81), “A momentum style with a three month holding period persistently out-performed the ALSI by around 9% per annum.” From this, it can be concluded that The Weather Effect is not an ideal solution to solve the business case created for obtaining a model which outperforms the market.

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CHAPTER 7: CONCLUSION

The two research questions raised by this research report resulted in no significant results. A predictive model could not be created to predict future returns on the JSE, indicating that previous work on The Weather Effect and the JSE could be a result of spurious correlations. This question of whether The Weather Effect can be utilised as a profitable market strategy on the JSE, according to investigation recommendation by Pizzutilo and Roncone (2016), was investigated and found not to be achievable by the use of the all-weather portfolio as an investment strategy.

7.1 Summary

A body of literature exists indicating the presence of The Weather Effect on various stock exchanges, including the JSE, as mentioned in Sections 2.3 and 2.5. This has been questioned by other authors replicating these studies, as reported in Section 2.4. These authors believe that the original studies suffer from data mining as a means for the studies to be published. With the increase of computing power, the likelihood of data mining will only increase (de Prado, 2015) and therefore the need for methodological pluralism (Lockett et al., 2014).

7.1.1 The Presence of The Weather Effect

This concern that was raised by the academic community provided the opportunity to create a novel methodology to address the shortcomings of the previously utilised methodologies. A model that forecast future returns of a portfolio was designed, but it was found that these portfolios could not successfully predict the future returns. This model was not only tested using NHST, as this was one of the concerns raised by the academic community, but graphical time series analysis was also performed, providing an insight which would not have been seen without this method.

From the results and discussion thereof in Chapters 5 and 6, it has been identified that the weather cannot be used to predict future returns on the JSE. The statistically significant results obtained in some instances in this research report

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are spurious and possibly due to instrumental variables. These instrumental variables are not identified in this study. The endogenous effects such as the Monday effect or January effect or macroeconomic factors as determined by other authors (Goetzmann et al., 2015), has been alleviated as a price relative has been included for the second research question, but could not be included in the first research question. The presence of The Weather Effect on the JSE is weak at best from 2001 until 2017.

An interesting finding is the seasonality of predicted stock returns of the model. The predicted seasonality indicates the existence of the Sell-in-May effect present on the JSE. Although this is not a new finding, an arbitrage opportunity is presented, which requires future research, please see Section 0.

7.1.2 Quintile Performance

The finding of arbitrage opportunities caused by weather-induced mood by authors (Dong & Tremblay, 2011; Fortado & Chiles, 2016; Novy-Marx, 2014; Schneider, 2014) could not be verified on the JSE. Due to the limitation in the decrease in rank, as shown in Table 6, The Weather Effect cannot constitute an investment style on the JSE.

7.1.3 Optimised Portfolio

From a business perspective, the utilisation of The Weather Effect to outperform the market, although possible through the use of optimised portfolios, is not an advisable investment strategy. There is evidence that the WeatherOptBest does outperform the ALSI and WeatherOptWorst, but this outperformance is limited when it comes to other styles and is only in the sample. There are styles that provide superior returns, such as the momentum effect (Muller & Ward, 2013).

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7.2 Limitations

Although a robust methodology was employed, this study had limitations, similar to previous studies into The Weather Effect. The study did not only use the NHST as per recommendations from Wasserstein and Lazar (2016). Deductive reasoning has been applied, as the weather influences mood and mood influences stock prices. By this thinking, a correlation between weather and stock returns are found then the weather must influence mood. Pizzutilo and Roncone (2016) argued that using stock returns as a proxy for the influence of the weather on investor mood is “not the most correct way” (p. 27), but it is argued that it is “the best approach in practical terms” (p. 27) in addressing the behavioural finance literature.

The methodology utilised did not account for the varying degree of significance of the weather betas. These betas were used in equation five as predictive measures, and therefore a different degree of accuracy led to a varying degree of accurate results in weather expected returns. In Section 6.3 the betas were identified as having little predictive power over the future returns. Each all-weather portfolio was assumed to have equal influence by the weather factors.

Investigation of other trading phenomena on the returns was excluded in this study. Possible endogeneity could be the driver of the performance of some if not all of the portfolios. Comovements of the stocks within the weather portfolios created by other anomalies (Wahal & Yavuz, 2013) such as the size-effect and momentum-effect (Novy-Marx, 2014) were not studied and might have impacted the results. The decrease in resource stocks and recovery thereof was not successfully attributed by the portfolio. It is not foreseen that this is a significant flaw, as the robust methodology employed would care for these to a degree. The results found did not raise any concerns that the method is lacking in this regard, as the results are not statistically significant.

As indicated, transaction cost in the monthly rebalancing was excluded. As the recommendation of not utilising The Weather Effect was made as a style investment, no further investigation into the cost of the portfolio was performed.

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South Africa experiences geographically diverse weather patterns, with the JSE located in Johannesburg. Other studies in The Weather Effect focussed on regions with similar weather patterns, such as ones performed by Schneider (2014) and Goetzmann et al. (2015).

Furthermore, no focus was given to higher significant weather beta stocks. A portfolio comprising of these could be seen as predicting future returns more accurately, but lacks a means by which the market could be outperformed.

The exclusion of newer companies has been performed as there is a 60-month listing requirement for the weather betas was a hurdle before the stock could be included into any of the portfolios. Loughran and Schultz (2004) argue that lightly newer firms are more influenced by the weather. There is, therefore, a chance that stocks which could predict future returns better has been omitted from the portfolios.

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7.3 Future research

This research report has found that limited research on The Weather Effect and the use of behavioural finance as a measure of style based investing on the JSE exists.

7.3.1 Behavioural Finance

Apergis and Gupta (2017) argue that the JSE is not as efficient as deemed by literature. Further research into market efficiency since 2008 should be carried out, as this could not be verified by the methodology used in this research report. This market efficiency investigation would lead to the influence of behavioural finance on the JSE, as the divergence from the EMH can be seen to create arbitrage opportunities.

Further investigation into other behavioural effects on the JSE is recommended. The continual increase in some of the weather portfolios gives rise to the possibility that there are other endogenous factors which could predict stock returns more accurately than The Weather Effect. Siganos et al. (2017) argue that high divergence of sentiment can be measured, which would influence stock market trading. Studies on perceived mood on social media, as one such a behavioural finance factor, could prove to be a more reliable predictor of stock returns.

Further investigation into the phenomenon in 2015 on the JSE, where there was a sudden drop in stocks is recommended. The research performed by this research report indicates that this could be ascribed to the performance of resources during 2015 and 2016. This market anomaly could have significant influences on other investment styles during the period.

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7.3.2 The Weather Effect

The inclusion of instrumental variables could remove the endogeneity created by the models. One of the possible variables which could be analysed is the inclusion of volatility in the model, as the time period preceding rebalancing could have a significant influence on the results. Bassi et al. (2013, p. 1845) found that "good weather conditions promote risk-taking behaviour" and although an attempt was made to leverage from this finding, the inclusion of volatility might have influenced the results. Investigation of volatility changes as a result of The Weather Effect, as proposed by Kang et al. (2010), was not investigated by this study.

Although there is very weak evidence of The Weather Effect, the investigation of market timing could prove to be advantageous. Seasonality of the stock exchange was found by this study. Kamstra et al. (2003) proposed a market timing technique with the utilisation of SAD. Although SAD influences might only be weak on the JSE, there appear to be superior seasonal returns which could be exploited. In the study of Kamstra et al. (2003), moved funds from one stock market to another during the autumn and winter, delivered superior returns. The proposed investment strategy would leverage on the seasonality influences on the JSE as found in this study.

Other research techniques to evaluate The Weather Effect, such as the ones utilised by Goetzmann (2015), by looking at a granular level of investors could lead to conclusive evidence of the existence of The Weather Effect on the JSE. This would increase the behavioural finance literature, as per request of Hirshleifer (2015), and further investigation into the EMH and arbitrage opportunities created thereby.

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APPENDIX A

Gordon Institute of Business Science
University of Pretoria

20 July 2017

Herman Steyn

Dear Herman,

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee

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