Gordon Institute of Business Science
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Risk parity and volatility timing on the Johannesburg Stock Exchange

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A research project proposal submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

7 November 2018

Abstract

Risk parity has been described as a relatively new approach to portfolio creation that has been gaining popularity (Sullivan, 2010). Under risk parity, the efficient portfolio is created by weighting assets by their risk rather than by their market value. The resulting risk parity portfolio is then combined with either borrowing or lending the risk-free asset to achieve a desired mean-variance outcome.

Volatility-timing is a market timing technique that seeks to exploit a weak relationship between short-term volatility and short-term return to improve the mean-variance outcome of a portfolio. The study examined the effect of volatility-timing on a risk parity portfolio to document the effect on the JSE. This serves to broaden the understanding of volatility timing and explore practical investment opportunities.

A risk parity portfolio was created using index funds over the last 18 years to compare performance with a 60/40 benchmark. In addition, differing methods of leverage application were explored, including a volatility-timing method to identify an optimal leverage methodology.

Risk parity was found to provide no risk-adjusted benefits to portfolio creation over the 60/40 portfolio. In addition, the approach to applying leverage, including a volatility-timed approach, provided no opportunity to capture excess returns.

Keywords

Risk parity, volatility timing, equal volatility, leverage

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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1.1. Research title

Risk parity and volatility timing on the Johannesburg Stock Exchange

1.2. Introduction - Background

In his 1959 book on portfolio selection, Harry Markowitz produced a model for portfolio selection. In this model he assumes investors are risk averse and care only about two factors when choosing portfolios, the mean return of their investment and the variance experienced in achieving that return . According to this model, given an expected return, an investor would select the portfolio with the lowest variance or given an expected variance, the investor would select the portfolio with the greatest expected return. Thus, Markowitz's model is often referred to as a mean-variance model (Fama & French, 2004).

The efficient market hypothesis (EMH) has, at its core, the hypothesis that it is not possible for an investor to make economic profits by trading on the basis of public information as the information will already be reflected in the price of the security (Jensen, 1978). Thus, in its semi-strong form, the EMH holds that a security's price fully reflects all available public information. The EMH may explain why many investors, attempting to achieve better mean-variance outcomes than the market, fail. However, market anomalies not consistent with EMH exist, as discussed by Jensen (1978).

Should the EMH hold true, the capital asset pricing model (CAPM) shows that investors will maximise their mean-variance outcomes by combining an efficient portfolio with either borrowing or lending the risk-free asset (Fama & French, 2004). The EMH would govern that the efficient portfolio must be a portfolio of all risky assets weighted by their market value, referred to as the market portfolio. The CAPM advocates that investors seeking a mean-variance maximizing portfolio will combine the market portfolio with either borrowing or lending the risk-free asset (Fama & French, 2004).

In attempts to exploit the market anomalies found in testing the EMH, investors have developed many different investment styles and strategies. Many of which seek to maximise the mean-variance trade-off investors face by advocating a superior asset allocation strategy to that of the market portfolio. A relatively new approach to asset allocation that is gaining popularity is called risk parity (Sullivan, 2010). Under risk parity, the efficient portfolio is created by weighting assets by their risk rather than by their market value. This results in a portfolio that carries equal risk in each asset class. The resulting risk parity portfolio is then combined with either borrowing or lending the risk-free asset to achieve a desired mean-variance outcome.

A significant characteristic of risk parity, as an investment strategy, results from balancing asset weights by risk. This results in a larger portion of low-risk assets necessary to balance out the smaller portion of high-risk assets. This means that the resultant efficient risk parity portfolio is a relatively low risk portfolio which must be combined with leverage, or borrowing at the risk-free rate, to achieve acceptable total portfolio riskiness (Asness, Frazzini, & Pedersen, 2012). When leverage is used, additional risks apart from portfolio volatility are introduced. These include the forced sale of assets to meet margin calls, which most often happen in adverse market conditions, exacerbating the effect of negative price movements. Leverage also introduces the possibility of experiencing losses beyond the full amount of capital invested (Jacobs & Levy, 2012). This may result in a mean-variance analysis which seems positive when assessing returns in the light of volatility alone, but which does not account sufficiently for real portfolio risk.

As the efficient risk parity portfolio is a lower-risk portfolio, a large portion of total return is generated by the leverage applied to the portfolio. The leverage applied is also responsible for setting the total portfolio risk. The investor must make decisions regarding how much total risk they are willing to undertake and whether the total portfolio risk should be adjusted based on market conditions. A market timing strategy, developed by Moreira and Muir (2017), based on volatility-timing seeks to exploit the weak relationship between volatility and expected return in the short-term. To exploit this anomaly, total risk exposure was reduced during times of high volatility and increased during times of recent low volatility (Moreira & Muir, 2017).

This finding may represent an opportunity to increase the mean-variance outcome of the risk parity portfolio by altering the amount of leverage applied during different market conditions.

1.3. Research Problem

Risk parity is a trading strategy growing in prominence in the United States of America with the possibility to greatly enhance the mean-variance trade-off for investors, however, it has not been extensively tested or implemented in the South African market. While prior studies into risk parity have matched the total portfolio risk to a benchmark portfolio (Asness et al., 2012), the volatility timing strategy has not been applied to dynamically alter total risk parity portfolio risk in the pursuit of greater mean-variance results. Consideration of this effect could lead to a more effective trading strategy.

1.4. Significance of research

This research consists of two major elements, firstly it will add to the body of knowledge on risk parity as an investment strategy with particular value in extending the research to the JSE. Secondly it will examine the effect of implementing a volatility managed strategy on a risk parity portfolio.

1.4.1 Academic rational

This research will be essentially a combination of the research done by Moreira & Muir (2017) and Asness et al. (2012)

The prior work done by Asness et al. (2012) examining risk parity as a trading strategy warrants repeating in the South African context as the JSE differs significantly from the universe of American stocks and bonds. This is particularly relevant when investigating risk parity as the strategy relies heavily on leverage and the availability of financial instruments to lever portfolios. While South Africa has a sufficiently advanced financial exchange to facilitate the leverage through futures contracts, these are not subject to the same liquidity as in US markets. This may affect the viability of risk parity when accounting for transaction costs in developing markets. In addition, unknown structural differences in the JSE may affect the viability of risk parity as an allocation strategy.

The combination with the work done by Moreira & Muir (2017) will add to the available literature on volatility managed strategies as risk parity was not included as an investment style that was examined by the authors. This combination will also add to the literature available on risk parity which does not seek an optimal risk level but rather matches the risk of the risk parity portfolio to a benchmark portfolio, the value weighted market portfolio in the case of Asness et al. (2012). This benchmarking is done to compare the mean-variance profile of risk parity directly with other investment strategies but does not add to an understanding of an optimal method of applying leverage given differing market conditions.

1.4.2 Business rational

The financial times reports that typical estimates of the industry size of risk parity investing range from $200 billion to $600 billion, depending on definitions (Wigglesworth, 2017). This large market size demonstrates the markets willingness to embrace a new investment philosophy that can improve mean-variance outcomes. This has implications for real world investment managers should the strategy outperform the mean-variance outcomes of more traditional investment portfolios on the JSE. The research also seeks to determine optimal leverage levels given specific market conditions which may improve on the fixed risk level or targeted benchmark risk level strategies currently employed in risk parity portfolios. Ultimately this may provide South African investment firms with meaningful improvements on an internationally successful investment strategy.

1.5. Research purpose

The purpose of this research is to establish the commercial viability of risk parity as an investment strategy on the JSE. Does risk parity provide a greater return for the same volatility than a benchmark portfolio? Does this benefit still exist in the light of leverage costs? This research will also establish whether dynamically adjusting total portfolio risk based on current market volatility improves the mean-variance of the risk parity portfolio.

This will require (i) the computation of the relative mean-variance benefit of the risk parity portfolio, if any, over a benchmark portfolio and (ii) an investigation into the optimal leverage to be applied given current market conditions.

In the study concluded by Asness et al. (2012) the increase in Sharpe ratio for the risk parity portfolio was 0.27 which would give an investor with an average volatility of 10, a 2.7% benefit per annum over investing in the value-weighted market portfolio. This research will establish whether such benefits of risk parity exist on the JSE and will provide insight into possible gains from following a volatility-managed portfolio strategy.

1.6. The scope of the research

The scope of this research will be limited to financial instruments traded on the JSE. In line with prior studies conducted, the asset classes that will be included in the risk parity portfolio will be limited to two classes, namely stocks and bonds (Asness et al., 2012). The stock and bond portfolios will be made up of an index of securities rather than testing any style effects of security selection within the stock and bond portfolios. The research will consider the effects of leverage costs on the outcomes to provide a real-world trading scenario that could be implemented.

CHAPTER 2. Literature Review

2.1. Introduction

The investor who wishes to create a portfolio will go through a two-stage process to arrive at the construction of that portfolio. The first stage begins with experiences and observations, which lead to beliefs concerning available securities and future performances. In the second stage, the investor will utilise their beliefs about available securities and future performances to inform their choice of portfolio (Markowitz, 1952). This paper is focused on the second phase, specifically, methods of portfolio creation.

2.2. Modern portfolio theory

In his seminal paper, published in 1952, Harry Markowitz laid the foundation for modern portfolio theory as we know it today. Markowitz formalised the mean-variance framework which suggests that investors are risk averse and will seek outcomes that maximise risk-adjusted returns.

Markowitz considers the rule that the investor seeks to maximise expected returns and rejects this as a hypothesis to explain investor behaviour. This rule never implies that there is a benefit to be gained through diversification. The benefits of diversification are both observed and sensible and as such, any rule of behaviour which does not take into account the superiority of diversification should be rejected (Markowitz, 1952). Were this rule sufficient, an investor would be justified in creating a portfolio that only existed of one security, the security with the greatest expected return. A portfolio that combined two securities with the same expected return would not be superior to the single security portfolio.

In response to this, Markowitz suggested a better rule, one which states that the investor should diversify their funds amongst those securities that have the greatest expected return. This rule assumes that there is a portfolio which would both maximise expected return and minimise variance of returns in achieving this return. This does not imply that the portfolio with the greatest expected return is also the portfolio with the lowest variance but rather that there is a rate at which the investor can gain return by taking on greater variance or reduce variance by sacrificing return

(Markowitz, 1952). This implies that there is not one single portfolio that maximises the mean-variance framework but rather an efficient set of portfolios whereby return is maximised for differing levels of variance.

Tobin (1958) added to portfolio theory by incorporating not only risky-assets but also a risk-free asset. This led to the seminal result known as the Tobin Separation Theory which has been described by Markowitz as the first Capital Asset Pricing Model (Markowitz, 1999). The Tobin Separation Theory showed that among efficient portfolios containing cash, the proportional composition of the risky asset was independent of their aggregate share of the investment balance (Tobin, 1958). This meant that it was possible to view the mean-variance efficient risky asset as a single non-cash asset which investors will then combine with cash to achieve their desired portfolio variance. This holds that investors with a greater level of risk-aversion will hold a combination of cash and the risky-asset, favouring higher levels of cash than a less risk-averse investor.

Similarly to Tobin, Sharpe (1964) posed a model consisting of risky assets and a risk-free asset, however where Tobin assumed that the investor could invest at the risk-free rate, Sharpe assumed that the investor could both invest and borrow at the risk-free rate (Sharpe, 1964). Although this difference in assumptions is seemingly small it led to a substantial difference in their conclusion. Sharpe showed that if investors can borrow or invest at the risk-free rate, then all efficient portfolios described by Markowitz would consist of a single combination of risky assets, perhaps with borrowing or investing at the risk-free rate. This holds that, in equilibrium, the market portfolio is the only efficient portfolio (Markowitz, 1999).

2.3. Efficient Market Hypothesis

With Modern portfolio Theory as a backdrop, could investors achieve a consistent return greater than that of the market portfolio? In response to this, the efficient market hypothesis was formally defined by Fama (1970) which classifies a market as efficient when security prices fully reflect all available information. The EMH is defined in three forms (Fama, 1970)

- Strong-form market efficiency means that prices reflect all available information, even when investors or groups have monopolistic access to information relevant to price formation

- Semi-strong-form efficiency means that prices reflect all obviously publicly available information
- Weak-form efficiency means that prices reflect all historical price or return sequences

Fama (1970) does acknowledge that strong-form efficiency would not be expected to be an exact model of the world and should rather be viewed as a benchmark however, tests conducted on the semi-strong form have supported this hypothesis (Fama, 1970). Should markets conform to semi-strong efficiency, there would be no implementable trading strategy to outperform the market as all prices would reflect all public information. Thus, the value weighted market portfolio would represent the efficient portfolio as each investor would purchase the stocks in measures related to their market capitalization (Fama & French, 2004).

There is growing evidence of inefficiencies in the market, observed by Jensen (1978). These inefficiencies represent opportunities for investors to obtain superior mean-variance outcomes by exploiting them. Superior mean-variance outcomes were shown to exist for stocks with low price to earnings ratios (Basu, 1977), small market capitilisations (Banz, 1981), trading with momentum based strategies (Fama & French, 2008) which were confirmed on the JSE (Hoffman, 2012) and for stocks with low Beta's (Frazzini & Pedersen, 2014). These findings represent departures from market efficiency however they may represent an incomplete model of the market rather than evidence that the market is acting inefficiently.

The existence of these inefficiencies is of extreme practical importance to investors as they allow for the possibility of achieving mean-variance outcomes in excess of those of the market which is a goal for any active investor.

2.4. Institutional investment in practise

Modern Portfolio Theory has provided a framework for portfolio construction that has been built upon over decades. Given that the efficient frontier described by Markowitz has been presented as a conceptual framework and the availability of a procedure to compute it is widely known, its lack of acceptance by investment practitioners as a tool for active equity investment management has been described as a "puzzle of modern finance" by Michaud (1989).

Investors in practise rarely adhere to the framework as many investors are constrained by the leverage that they are willing or able to take (Frazzini & Pedersen, 2014). The topic of leverage will be discussed further in section 2.5.4. Many mutual funds will offer a “normal” fund which may invest 60% of its value in stocks and 40% of its value in bonds whereas, the “aggressive” fund would invest 90% of its value in stocks and only 10% of its value in bonds. If the “normal” fund were to be mean-variance efficient then the investor would be able to leverage the “normal” fund to achieve a better mean-variance trade-off than the “aggressive” portfolio with a tilt towards stocks (Frazzini & Pedersen, 2014).

Given that the market portfolio may not provide the adequate levels of absolute return as required by investors, their only recourse other than combining it with leverage would be to deviate from the efficient portfolio, sacrificing diversification, to gain higher exposure to high-beta assets. This high-beta portfolio would by definition not be the market portfolio and would thus not lie on the capital market line making it inferior to a combination of the risk-free asset and market portfolio (Asness et al., 2012).

Markowitz (1952) did note the importance of the estimates that are used when compiling the mean-variance optimizing portfolio. In practise this can prove to be one of the largest challenges limiting the real world implementation of Modern Portfolio Theory (Michaud, 1989). In order to create a mean-variance optimized portfolio, the investor will be required to make ex-ante estimates of future return and variance. Although models such as the CAPM exist to define the relationship between expected return and risk, they are inexact and rely on predictions based on historical information. In practise, realised levels of risk and return may vary significantly from their ex-ante predictions resulting in the predicted mean-variance optimized portfolio differing from the actual mean-variance optimized portfolio. This susceptibility to estimation error and the resulting false optimum portfolios have held back widespread adoption of a pure mean-variance approach to asset allocation (Michaud, 1989).

2.4.1 The 60/40 portfolio

As a pure mean-variance approach has proven to face challenges in real-world implementation, many investors will use a heuristic approach to portfolio creation. A common approach amongst institutional pension funds is commonly referred to as a 60/40 portfolio, holding roughly 60% in stocks and 40% in bonds. This portfolio is designed to achieve the 8%-9% long-run return, in American markets, that pension funds require to fund their obligations (Chaves, Hsu, Li, & Shakernia, 2011). Although many assets classes such as property, emerging market securities and commodities have been added to the investment universe open to pension funds, their adoption has been modest despite the mean-variance optimization that these asset classes could provide through diversification (Chaves et al., 2011).

As the 60/40 portfolio is chosen with absolute return as the primary goal, this heuristic falls into the rejected rule for portfolio creation described my Markowitz (1952). The 60/40 portfolio targets returns and as such does a poor job of diversifying risk as the high-risk assets are over-weighted, leading to a disproportionately large share of portfolio risk attributed to equity volatility (Qian, 2011). Despite the mean-variance inefficiency predicated by modern portfolio theory, the 60/40 portfolio remains as a popular heuristic for asset allocation.

2.5. Risk Parity

Diversification is a concept that is ubiquitous in financial markets. When used correctly it offers the benefit of reducing risk without reducing expected return (Qian, 2011). Risk parity is a diversification strategy that aims to create a portfolio with equal risk contributions from each of the assets or asset classes in the portfolio (Bai, Scheinberg, & Tutuncu, 2016). In a simple example, should an equity portfolio have a volatility three times higher than a bond portfolio, the resultant risk parity portfolio would hold 25 percent equity and 75 percent bonds, representing a three times greater holding in bonds to balance their risk contribution (Clarke, De Silva, & Thorley, 2013). This is in contrast to the more common method of portfolio creation by diversifying across asset class based on value (Asness et al., 2012). The 60/40 portfolio whereby 60 percent on value held in equities and 40 percent of value held in bonds is easily recognizable as a real world example of diversifying by value (Anderson, Bianchi, & Goldberg, 2013).

2.5.1 Early Studies

Risk parity is a strategy that falls under the umbrella term of risk-budgeting, which is concerned with the analysis of portfolios on risk contribution grounds rather than portfolio weights (Maillard, Roncalli, & Teïletche, 2010). The impact of risk on portfolio performance has been shown repeatedly. Both Booth and Fama (1992) and Fernholtz, Garvey and Hannon (1998) showed that improved returns could be achieved by diversifying the risks in portfolios.

Qian (2006) was able to show that risk contributions have financial significance as they have shown predictive ability when considering each position's contribution to possible losses, even though existing measures of risk have undergone scrutiny. Sharpe (2002) criticised measures of risk contribution that relied on marginal risk contribution as risk, expressed as standard deviation, is not additive. Chow and Krirtzman (2001) however found standard deviation to have financial meaning as it enabled investors to make efficient use of leverage an maintain chosen ex-ante standard deviation levels when operating within the mean-variance framework.

2.5.2 Risk parity construction

The risk-based asset allocation strategies used in risk parity deviate from the classical mean-variance approach as they do not incorporate expected returns into the allocation decision (Bai et al., 2016). However, as expected returns prove to be difficult to estimate accurately, risk based approached are a more robust solution to achieve an ex-post efficient portfolio (Maillard et al., 2010).

Risk parity as a portfolio construction strategy attempts to diversify the portfolio by risk with equal risk contributions by each asset in the portfolio. In its simplest form, risk parity portfolio construction ignores correlations between asset class and was proportionally a simple inverse of the asset class volatility (Asness et al., 2012). This strategy while simple to compute would only be mean-variance maximising if all assets had identical Sharpe ratios and correlations (Maillard et al., 2010).

Qian (2006) formalized an alternate version of risk parity portfolio creation that included class correlations and adjusted asset class weights so that each asset class had the same contribution to portfolio risk. Further to this method, Qian (2011) developed an allocation strategy that he dubbed Dynamic Risk Parity which would include varying Sharpe Ratios into the portfolio creation algorithm.

A further method of achieving parity called Diversified Risk Parity was developed by Bender, Briand, Nielson and Stefek in 2010. In this method, risk was decomposed into the risk factors that a security was exposed to. Parity was then achieved by balancing the exposure to underlying risk factors such that each factor did not present a larger portion of portfolio risk. This method was found to achieve greater ex-post risk equalisation (Bender, Briand, Nielsen, & Stefek, 2010).

This evolving understanding of what defines parity results in many interpretations of the best method to achieve parity (Clarke et al., 2013). The studies that developed these differing methods of achieving parity present the methods as a means to achieve a more complete balancing of risk. They do not however evaluate the returns generated by each method. With little evidence of superior returns using alternate methods and, in line with research conducted by Asness et al. (2012), this paper will incorporate the simplest form of parity creation being financially intuitive and easily implemented by a range of investors.

2.5.3 Risk Parity and Modern Portfolio Theory

The risk parity practice of diversifying by risk rather than value deviates from the EMH as it allocates a larger percentage of the portfolio to low risk assets than would be included in the market portfolio. This is justified by proponents of risk parity by viewing diversification from the perspective of risk and not market capitalisation, as in the market portfolio. Given the high levels of volatility in stocks, the total volatility in the portfolio performance of a 60/40 portfolio is dominated by the volatility in equity markets. Thus, although the 60/40 portfolio may look well diversified by value, when viewed through the perspective of risk it offers little diversification (Asness et al., 2012). When viewing the 60/40 portfolio by risk rather than portfolio weight, the higher risk equity portion can contribute more than 90% of total portfolio risk (Qian, 2011).

The risk parity investor must still justify the deviation from the market portfolio as the intuition of diversifying by risk does not ensure superior performance. Should the equity risk premium be large enough, the risk parity investor should happily give a disproportionately large part of their risk budget to equities. The resulting theoretical justification of risk parity must indicate a superior mean-variance trade-off for low risk assets than for high risk assets (Asness et al., 2012).

Without this reliance on market inefficiencies, the risk parity portfolio would only be the mean-variance maximizing portfolio if the securities had identical Sharpe ratios and identical correlations (Maillard et al., 2010). This would mean that in practice the risk parity portfolio is unlikely to be the mean-variance maximizing portfolio. This raises doubt as to the effectiveness of the risk parity strategy and it’s likelihood of being the ex-post mean-variance efficient portfolio (Agapova, Ferguson, Leistikow, & Meidan, 2017). This problem with risk parity identifies the strategy’s departure from the EMH and the resulting reliance on market inefficiencies to be profitable.

2.5.4 Leverage

The notion of applying leverage to a low-risk portfolio is not a new one and dates back to Jensen, Black & Scholes (1972) who provided empirical evidence that low beta equities provided greater risk adjusted returns than the CAPM would predict. A theory of leverage aversion was developed by Frazzini & Pedersen (2014) to explain the low-beta market anomaly.

The basic premise of the CAPM is that investors choose to invest in a mean-variance maximizing portfolio and then either borrow or lend at the risk-free rate to achieve their desired level of total portfolio risk. However, many different classes of investors are constrained in their ability to take on leverage, such as individuals, mutual funds and pension funds (Frazzini & Pedersen, 2014). This is apparent in an investigation into South African collective investment schemes where the “aggressiveness” of the funds is altered by altering the allocation of those funds to equities, rather than applying leverage to an efficient portfolio.

This behaviour of preferring high-beta assets suggests that high-beta assets require a lower risk adjusted return than low-beta assets, which then require leverage to achieve high enough risk (Frazzini & Pedersen, 2014). This theory of leverage aversion predicts that investors seeking high returns and willing to take on high risk will deviate from the efficient market portfolio, suggested by the CAPM, and instead will overweight high-risk assets rather than applying leverage.

This was found empirically as the security market line or SML, a prediction of risk and return for securities resulting from the CAPM, was found to be too flat compared to theoretical CAPM predictions (Jensen, Black, & Scholes, 1972). The SML was found to be better explained by the CAPM model that included restricted borrowings than the standard CAPM (Black, 1972). This finding extended into the credit markets where a levered portfolio of highly rated corporate bonds outperformed a de-levered portfolio of low-rated bonds (Frazzini & Pedersen, 2014).

A common misconception of leverage is that as long as investors expect a level of portfolio return in excess of the borrowing costs of leverage, leverage could be applied at ever-increasing levels to achieve ever increasing returns. This would hold true in a world of constant returns; however, investment returns are not constant and returns from ever-increasing leverage are bounded. The downside of increased portfolio leverage is the cost of volatility drag, which is the difference between arithmetic and geometric average returns (Booth & Fama, 1992). This holds that as leverage is increased, the volatility drag increases as the increase in the volatility of levered assets carry more risk (Scott & Watson, 2013).

In order to enhance portfolio returns, the spread of levered returns over borrowing costs must be greater than the variance of the levered return. It is clear that higher borrowing costs will have a negative effect on the prospects of applying leverage to gain excess returns.

2.5.5 Empirical performance

Maillard et al. (2010) tested a risk parity portfolio, that they referred to as an equal-weighted risk contribution portfolio, against a minimum-variance portfolio as well as an equal weighted portfolio as the benchmarks. These benchmarks were chosen to reflect viable alternatives when constructing portfolios based on risk. The risk parity portfolio was created in line with the method described by Qian (2006), incorporating asset correlations when determining risk weightings. The risk parity portfolio achieved a Sharpe ratio of 0,67 while the minimum variance portfolio achieved 0,49 and equal-weighted portfolio achieved 0,27 when creating a globally diversified portfolio. The risk parity portfolio was however beaten by the minimum variance portfolio when portfolios were created using USA equities and when portfolios were created using agricultural commodities (Maillard et al., 2010).

Chavez et al (2011) tested a number of portfolios, including a risk parity portfolio, over a period spanning 1980 to 2010. The other portfolios included equal weighted, minimum variance as well as 60/40 portfolios. The risk parity portfolio was created using two indices, the S&P 500 index and the Barclays Capital Live bond index. When compared to a comparative 60/40 portfolio using the same indices, the risk parity portfolio achieved a higher Sharpe ratio at 0,62 compared to 0,50 for the 60/40 portfolio. The risk parity portfolio achieved a lower total return which would be expected with risk parity's higher allocation of bonds. To achieve a comparable total return, leverage would need to be applied.

When incorporating nine asset classes the risk parity portfolio achieved a greater Sharpe ratio than the minimum variance portfolio and achieved the same Sharpe ratio as the equal weighted portfolio. When compared to a 60/40 approach using nine asset classes, the Sharpe ratio of the 60/40 was 0,01 higher than the risk parity portfolio (Chaves et al., 2011). This study showed that risk parity does not consistently outperform alternatives and the strategy may be very sensitive to the choice of asset class and the window of the study.

Empirical testing done by Asness et al. (2012) showed that a risk parity portfolio of US stocks and bonds outperformed the value weighted market portfolio over an 84-year period. The risk parity portfolio improved the Sharpe ratio by 0.27 which would equate to a 2.7% increase in annual return for an investor with a volatility tolerance of 10. This result was found to be statistically significant (Asness et al., 2012). A similar test was done by Anderson et al. (2013) using the same data set and while they also found that the risk parity outperformed the market portfolio, this outperformance was negated with the inclusion of transaction costs. This raises questions on whether the implementation of risk parity has real world advantages over competing investment styles.

Risk parity can be applied across asset class or within asset class. In a study performed by Sorensen and Alonso (2015) the S&P 500, a cap-weighted index was compared to a risk parity portfolio created using the same 500 stocks that formed part of the index, however weighted by their risk contributions so that no single stock was allocated more of the portfolio’s risk budget than any other stock. The study compared investment windows ranging from 1995 to 2014 and found that risk parity outperformed the index in 75% of all possible 3 year investment horizons and in 100% of all investment horizons longer than six years (Sorensen & Alonso, 2015).

Overall, these studies suggest that there may be tangible value to risk parity as an asset allocation strategy both on a risk-adjusted and total return basis with leverage employed. The literature does however, introduce questions about how asset classes, timeframe and transaction costs may affect the viability of risk parity as an investible solution.

2.5.6 Criticisms of risk parity

Although risk parity has shown empirical results, its critics note a lack of theoretical grounding for diversifying by risk. Although the approach is intuitively appealing as a method for achieving superior diversification, this does not guaranty superior returns (Thiagarajan & Schachter, 2011). Lee (2011) highlights that the assumptions on which risk parity are based are themselves flawed as the objective is diversification while ignoring the estimates of return. Lee (2011) suggests that investors do not seek diversification for its own sake but rather use diversification as a tool for achieving superior returns.

Inker (2011) raises a concern that using historical standard deviation as a measure of risk may result in a portfolio that the investor believes to be safe but is anything but that. The mean-variance analysis used to determine outperformance by risk parity takes volatility as the only form of risk. This point is further compounded by the nature of financial markets and risk. The market conditions where risk is at a maximum, recessions and market crises, occur too seldomly to allow accurate expectations of the losses from such an event. Furthermore, securities that had proven to be safe havens during one crises may not be during the next, as was the subprime mortgage market before 2004 (Inker, 2011).

Risk parity's resulting portfolio that is overweight low risk assets results in a portfolio that may be diversified by risk but carries a low total portfolio risk and expected return. In a similar approach as suggested in the CAPM, the resulting risk parity portfolio must then be levered, increasing portfolio volatility, in order to obtain a desired total portfolio risk and return level (Asness et al., 2012). The risks introduced by adding leverage are not captured in a mean-variance analysis, taking standard deviation as a complete measure of risk, which may reduce the effectiveness of evaluating levered portfolios against unlevered portfolios with mean-variance analysis (Jacobs & Levy, 2012). Leverage introduces further risks including the risk of margin calls resulting in forced selling to meet margin obligations, turning temporary losses into permanent losses. Leverage also magnifies errors in risk estimation turning manageable errors into catastrophic errors resulting in not only a complete loss capital but potentially losses in excess of the original capital invested (Inker, 2011). These risks are not captured by a standard deviation measure.

2.6. Volatility based strategies

Volatility has played a central role in financial literature as a key component in optimal portfolio selection, asset pricing and risk management (Fleming, Kirby, & Ostdiek, 2001). Volatility in this case refers to the standard deviation in the daily returns achieved.

2.6.1 Early studies

Evidence of a positive relationship has long existed between the expected risk premium on common stocks and the predictable level of volatility (French, Schwert, & Stambaugh, 1987). Early studies have however focused on the statistical performance of volatility models giving less attention to the economic significance of time-varying predictable volatility (Fleming et al., 2001). These volatility models have developed over time, starting with Engle (1982) developing an autoregressive conditional heteroskedasticity (ARCH) model evolving to a generalised ARCH (Bollerslev, 1986) and exponential ARCH (Nelson, 1991) which model volatility to asset returns.

Active investors seek relationships that exhibit predictive power in order to enhance estimates of future risk and return. As market volatility proves to be more accurately measured than expected return, investors should be able to more accurately predict volatility than returns (Merton, 1980). It comes as no surprise then that investors exhibit a greater ability to time volatility than to time returns.

Busse (1999) tests a hypothesis that there is a negative relationship between market return and volatility which was confirmed empirically with data from 1985 to 1995. This incentivises investors to reduce market beta in anticipation of higher levels of market volatility. Busse (1999) finds that 80 percent of the 230 mutual funds sampled will attempt to time volatility in this way. Busse (1999) also identifies a strong positive relationship between funds that do reduce systematic risk when conditional volatility is high and funds that earn superior risk-adjusted returns.

2.6.2 Short term predictability

The positive relationship between risk premium and volatility holds true in the long term but breaks down in the short term (Moreira & Muir, 2017). The ability of firms to forecast volatility has improved dramatically over time with the availability and inclusion of more data. This has included moving from calculating volatility using daily return data to employing an approach called "realized" volatility that calculates volatility using intra-day returns at very short intervals (Fleming, Kirby, & Ostdiek, 2003). Forecasting volatility has also show to be highly accurate as volatility turns out to be highly predictable (Andersen, Bollerslev, Diebold, & Labys, 2003) as realized volatility has been shown to be lognormally distributed and daily returns, when standardized by realized volatility, are also approximately normal (Fleming et al., 2003).

2.6.3 Empirical performance

Researchers have long been aware of the predictable nature of volatility in the short term. However, studies of standard volatility models have shown that they exhibit a low explanatory power, responsible for a small fraction in the variation of squared returns (Fleming et al., 2001).

Fleming et al. (2001) showed that the predictability captured by volatility modelling is not only economically significant but exploiting this by employing a volatility-timing strategy based on one-step-ahead estimates of volatility significantly outperform unconditionally efficient static portfolios for the same targeted expected return or targeted volatility (Fleming et al., 2001).

Foran and O'Sullivan (2017) examined the UK mutual fund market for evidence of volatility timing among mutual fund managers. Out of their sample of 1141 actively managed mutual funds, only six percent of fund managers showed an ability to time volatility. More concerning was that although volatility relationships have been shown to persist, the skill of fund managers to time volatility was not found to persist in their sample.

A study completed by Giambona and Golec (2009) found that it was pro-cyclical volatility timing, that which increased market beta when conditional volatilities were high, that produced greater returns. This was attributed to the market compensating these funds for taking on more risk in the face of high volatility.

The predictable nature of volatilities in the short term allowed Moreira & Muir (2017) to test the relationship between forecasted volatility and future returns. The results of their study found that there is a weak relationship between risk premium, or price, and volatility in the short term. This led Moreira and Muir (2017) to conclude that the pro-cyclicality, advocated by Gaimbona and Golec (2009), was in fact not rewarded with additional return, and as such, a counter-cyclical approach would provide a higher mean-variance outcome. Their study found that a counter-cyclical approach yielded a 25 percent increase in the Sharpe ratio compared to the buy-and-hold portfolio.

2.6.4 Mean variance implications of short-term volatility

If an increase in volatility does not forecast an increase in returns in the short term the mean-variance trade-off will deteriorate in periods of high volatility as investors are not compensated for the additional risk (Moreira & Muir, 2017). Empirical studies have failed to show a simple positive relationship between conditional market returns and conditional market volatility [see, e.g., Campbell (1987), Glosten, Jagannathan and Runkle (1993) and Whitelaw (1994)]. This suggests that investors would be able to increase risk-adjusted returns by reducing market exposure when conditional volatility increase (Busse, 1999).

As many measures of fund performance also include a measure of risk, such as the Sharpe ratio and Jensen's Alpha, managing the risk exposure of the fund is as important as the return characteristics (Busse, 1999). Gruber (1996) showed that the inflows that mutual fund managers receive are affected by the risk-adjusted performance, not only total return, that the fund achieves.

Criticisms of volatility strategies

Scruggs (1998) explored altering market exposure during times of high volatility and while this does reduce the investors exposure to market risk during this period, other risks could be introduced to the portfolio. These may include risks such as interest rate risks (Scruggs, 1998).

Conflicting results on the reward of either timing volatility to exploit pro-cyclical or counter-cyclical trends raises doubt as to whether there are gains to be realised or whether the results achieved in prior studies may be sensitive to investment period and asset class.

2.7. Conclusion

There is contradictory evidence regarding the real world effectiveness of risk parity as an investment strategy (Anderson et al., 2013). Researchers that has found risk parity to be a viable investment strategy have justified it as it has superior mean-variance trade-offs, being a greater level of return for a given level of risk. This measure of risk, however, does not factor the additional risks introduced by the use of leverage into the viability of the strategy (Jacobs & Levy, 2012). Risk parity has a strong theoretical basis for outperformance assuming the presence of leverage aversion. Risk parity should be able to exploit these market inefficiencies by utilising low-beta assets and applying leverage (Frazzini & Pedersen, 2014).

The optimal amount of leverage to apply to the risk parity portfolio, given underlying market conditions, has not been studied, with current empirical studies focussing on benchmarking alone. A timing strategy based on volatility has shown promise in other investment styles and may be able to add to the understanding of optimising the risk parity investing process in practise (Moreira & Muir, 2017).

CHAPTER 3. Research Hypotheses

This research will make a contribution to the existing literature on risk parity to examine whether risk parity is a viable investment strategy on the JSE and whether risk parity provides a greater mean-variance trade-off than the 60/40 portfolio, as observed by (Asness et al., 2012), on the JSE.

> Q1) Does an un-levered risk parity portfolio provide a greater cumulative return than the 60/40 portfolio on the JSE?

The un-levered risk parity and 60/40 portfolios will be compared using a graphical time-series of cumulative returns. The null and alternate hypotheses will be:

$H_{1^0} : R_{RPul} - R_{60/40} = 0$

$H_{1^A} : R_{RPul} - R_{60/40} <> 0$

Where R_{RPul} refers to the cumulative return of the risk parity portfolio and $R_{60/40}$ refers to the cumulative returns of the 60/40 portfolio.

This research will further aim to test a constant-levered method of applying leverage to the un-levered risk parity portfolio. The second research will be:

> Q2) Does a constant-levered risk parity portfolio provide a greater cumulative return than the 60/40 portfolio on the JSE?

The constant-levered risk parity and 60/40 portfolios will be compared using a graphical time-series of cumulative returns. The null and alternate hypotheses will be:

$H_{2^0} : R_{RPcl} - R_{60/40} = 0$

$H_{2^A} : R_{RPcl} - R_{60/40} <> 0$

Where R_{RPcl} refers to the cumulative return of the constant-levered risk parity portfolio and $R_{60/40}$ refers to the cumulative returns of the 60/40 portfolio.

This research will further aim to test a target-levered method of applying leverage to the un-levered risk parity portfolio. The third research will be:

> Q3) Does a target-levered risk parity portfolio provide a greater cumulative return than the 60/40 portfolio on the JSE?

The target-levered risk parity and 60/40 portfolios will be compared using a graphical time-series of cumulative returns. The null and alternate hypotheses will be:

H_{3^0} : R_{RPtl} - $R_{60/40}$ = 0

H_{3^A} : R_{RPtl} - $R_{60/40}$ <> 0

Where R_{RPtl} refers to the cumulative return of the target-levered risk parity portfolio and $R_{60/40}$ refers to the cumulative returns of the 60/40 portfolio.

This research will further aim to test a volatility-timing-levered method of applying leverage to the un-levered risk parity portfolio. The fourth research will be:

> Q4) Does a volatility-timing-levered risk parity portfolio provide a greater cumulative return than the 60/40 portfolio on the JSE?

The volatility-timing-levered risk parity and 60/40 portfolios will be compared using a graphical time-series of cumulative returns. The null and alternate hypotheses will be:

H_{4^0} : R_{RPvtl} - $R_{60/40}$ = 0

H_{4^A} : R_{RPvtl} - $R_{60/40}$ <> 0

Where R_{RPvtl} refers to the cumulative return of the volatility-timing-levered risk parity portfolio and $R_{60/40}$ refers to the cumulative returns of the 60/40 portfolio.

CHAPTER 4. Research Methodology

4.1. Research design

This research aimed to answer two main questions, firstly, whether risk parity was a viable investment strategy on the JSE and secondly, whether applying leverage in different methods, including a volatility-timing strategy, would improve the outcomes of the risk parity portfolio.

Both questions were answered using a quantitative methodology. The use of stock market data to analyse risk and return necessitated the use of a quantitative methodology in order to provide answers to the research questions. The financial portfolios were created and tested over time which makes this study quantitative by nature.

The philosophy of this research is positivism as it sought to find observable defined laws that can be tested (Saunders, Lewis, & Thornhill, 2009). This was evident in the research problems as defined trading rules were being compared and contrasted.

The approach this research took is a deductive approach as it sought to test theory already available in literature, thus the theoretical position had been developed prior to collecting the data (Saunders et al., 2009). The concepts studied such as risk parity, leverage, volatility and mean-variance analysis were well defined in literature and need not emerge for the study. Asness et al. (2012) had defined a risk parity trading strategy which was being tested together with a volatility timing strategy developed by Moreira & Muir (2017).

This study followed a mono-method approach as there was one data collection method and analysis procedure (Saunders et al., 2009). The data collection entailed collecting secondary data on which quantitative analysis was performed. This method best allowed for the analysis of the research problems.

This research was descripto-explanatory in nature. In this design the descriptive element sought to portray an accurate profile, on the JSE, of the risk parity strategy given by Asness et al. (2012). The explanatory element sought to establish the relationship between returns and volatility through a market timing strategy which had not been tested in risk parity portfolios (Saunders et al., 2009).

The strategy was quasi-experimental as it sought to establish causal links between two variables (Saunders et al., 2009), in this case volatility and return, however as the research had a time-series design which did not allow the researcher full control over the treatment exposure or influence of extraneous variables it cannot be classified as purely experimental and falls into the category quasi-experimental (Zikmund, Babin, Carr, & Griffin, 2008). The quasi-experimental strategy allowed the use of field data rather than simulated data, increasing the external validity of the design (Jensen, Fast, Taylor, & Maier, 2008).

This research was longitudinal as it examined returns generated over time and sought to understand changes in performance over time (Saunders et al., 2009). The research questions were answered by evaluating the effects of risk parity and differing methods of leverage application as an investment strategy by examining the return that these strategies would have produced over time.

This research was conducted using secondary data that is time-series based. This research used multiple source secondary data (Saunders et al., 2009) to compile returns and volatilities for financial assets over a multi-year period. Data was gathered from more than one database which makes the technique a multiple source technique.

4.2. Population

The target population for this research included all companies (stocks) and bonds listed on the JSE during the target period from December 1998 to August 2018. Saunders et al. (2009) characterises the population as the complete set of group members. This population was chosen as portfolios of South African stocks and bonds were constructed in order to test our hypotheses. These stocks and bonds were only selected from financial assets listed on the JSE. This population was chosen as it represents the assets that most investors have access to investing in (Ward & Muller, 2012). The date range was chosen as it represents over 18 years of data while still being easily accessible and reliable.

4.3. Unit of analysis

The unit of analysis can be defined as the members or elements of a population (Welman, Kruger, & Mitchell, 2005). The unit of analysis for this research evaluated elements of the population. The unit of analysis included stocks and bonds listed on the Johannesburg Stock Exchange throughout the sample period. Of particular interest were the cumulative portfolio returns resulting from varying portfolio creation strategies developed in the testing phase. The relative difference in cumulative portfolio returns were compared and analysed.

4.4. Sampling method and size

The sampling method employed was purposive, which is a non-probabilistic sampling technique whereby the sample selected is typical of the population and is considered to be illustrative and representative (Saunders et al., 2009). The method was necessary as the researcher's judgement was employed to select the sample. This judgement included selecting relevant indices out of the possible population in order for the results to be representative.

The sample of stocks was the JSE All-Share Index (ALSI). The ALSI comprises the largest 160 shares listed on the JSE and has been shown to represent 99% of the total market capitalisation of the JSE (Ward & Muller, 2012). The companies falling outside the ALSI were excluded as they wereconsidered to be either too small or too illiquid for the most investors (Ward & Muller, 2012).

The sample of bonds was the JSE All-Bond Index (ALBI). The ALBI comprises the top 20 vanilla bonds from across the full range of maturities, ranked dually by liquidity and market capitalisation. In related studies on risk parity portfolio construction, a bond index was used to comprise the bond portfolio (Asness et al., 2012).

The researcher's judgement was required as a probabilistic approach may have resulted in portfolio's that were not representative of the population or representative of what the majority of real-world investors would invest in.

4.5. Measurement instrument

As this research relied on secondary data, the researcher did not generate new data. To evaluate whether the secondary data could be used, the data set appropriately measured the variables necessary to answer the research question (Kimberlin & Winterstein, 2008). The chosen databases fulfilled this requirement as they included the relevant financial data needed to test the portfolio strategies. These databases of financial data were imported into Microsoft Excel where formulas, graphs and other data management tools were utilised to produce a financial model to test the portfolio construction techniques.

The Excel model ensured internal validity by testing whether the experimental variable (volatility) was responsible for any variance in the dependant variable cumulative returns (Zikmund et al., 2008). Excel allowed the inclusion of controls to increase the internal validity of the results. External validity was increased by ensuring the sample was representative of the population and the results extended to other market segments or groups of people (Zikmund et al., 2008). This was increased by selecting valid indexes to represent investment decisions as well as through the use of financial models which could be applied to multiple global investment scenarios.

When utilising secondary data, the reliability of the results are effected by the quality of the data source (Saunders et al., 2009). The financial data utilised was of high quality and was suitable for testing the research hypotheses which increases reliability. The data were verifiable across multiple sources and represent an objective historical account of the financial movements of the assets.

4.6. Data gathering process

The research relied solely on secondary data. Utilising secondary data involves reanalysing data that was collected for some other purpose (Saunders et al., 2009). The information and data required for this research was obtained from the IRESS database as well as the Sharenet database. The data included daily share and bond price observations as well as volatility measures. This data was uploaded into Microsoft Excel for analysis. Secondary data was required for the analysis of this research as, the alternative would have been to either create the portfolios with out-of-sample data and to track the actual returns over time which would take many years to arrive at meaningful results or would necessitate the use of simulated lab data which would negatively affect the external validity of the study. The financial data required to complete the study included, security and index prices, dividends paid and standard deviations.

4.7. Analysis approach

The data collected from the databases was uploaded into Microsoft Excel. The analysis of this data took place in four phases.

Phase one was to interrogate the data that has been gathered for anomalies. This was conducted using a time series analysis. The objective of time series analysis could be identified as description, explanation, prediction and control (Chatfield, 2004). In this instance it's use was primarily descriptive as any irregularities in the data would present themselves as spikes in the time series chart. These irregularities were then be checked for accuracy.

Phase two was the creation of the risk parity portfolio. The portfolio was made up of a combination of stocks and bonds. The portfolio was created to weight the risk equally between the stocks and bonds. As bonds are usually a lower risk asset there will generally be a greater percentage of bonds in the portfolio than stocks (Asness et al., 2012). The Risk Parity portfolio was rebalanced daily to ensure an equal risk allocation across the two asset classes. The portfolio construction was matched to prior work in risk parity investments done by Asness et al. (2012). The weights of each asset class were calculated using the following equation:

$$\mathcal{W}_{t,i} = k_t \hat{\sigma}_{t,i}^{-1}$$

Where

$\mathcal{W}_{t,i}$ is the weight of each asset class

k_t is a factor that controls the amount of leverage or the target volatility of the portfolio

$\hat{\sigma}_{t,i}$ is estimated as the 249-day rolling volatility of monthly excess returns to $t-1$

From the above equation, the relative weights of each asset class were calculated daily as the inverse of its volatility. This means that during times of high equity volatility, a greater percentage of bonds will be held than equities and vice versa. In research done by Asness et al. (2012), the average weight over their investment period was 15% in stocks and 85% in bonds. Similar weightings were expected in this research. This phase would allow for the completion of the first research question.

Phase 3 involved three different approaches to achieving the desired leverage in the portfolios, by manipulating k_t.

Approach 1 – Constant-Levered

A specified level of leverage was maintained throughout the duration of the period. k_t applied a fixed level of leverage to the un-levered risk parity portfolio to ensure that a constant, predefined level of leverage would be maintained over time. The predefined level of leverage was computed as the level of leverage required to achieve the same mean standard deviation in the constant-levered risk parity portfolio as the 60/40 portfolio. This would allow for a direct comparison of the cumulative returns of the two portfolios. This approach to setting the applied leverage would allow for the completion of the second research question

Approach 2 – Target-Levered

In this case, the benchmark would be the 60/40 portfolio. The target-levered risk parity portfolio would attempt to match the standard deviation of the 60/40 portfolio at each daily rebalancing point throughout the investment horizon. The targeting occurred with ex-ante information and as such did not match the realised standard deviation of the 60/40 portfolio completely at each rebalancing point.

A sigmoid function was used as an optimisation technique and was defined as:

$$k_t = \frac{1}{1+\exp -\left(\beta_1 \frac{\sigma_{RPtl}}{\sigma_{60/40}} + \beta_0\right)} \times \gamma$$

Where

k_t is the amount of leverage applied

β_1 is a regression coefficient

$\frac{\sigma_{RPtl}}{\sigma_{60/40}}$ is the standard deviation of the risk parity portfolio over the 60/40 portfolio

β_0 is the intercept

γ is a multiplier

The regression coefficient and intercept were solved for using an excel optimisation function and ensured that the mean standard deviation of the target-levered risk parity portfolio matched the mean standard deviation of the 60/40 portfolio over the investment horizon. The multiplier set the maximum amount of leverage that could be applied. The relative standard deviation was the predictor that changed at each daily rebalancing. This function resulted in an increase (decrease) in leverage when the standard deviation of the target-levered risk parity portfolio was below (above) the standard deviation of the 60/40 portfolio.

This was the approach used by Asness et al. (2012) which allowed for a direct comparison in the cumulative returns between the risk parity portfolio and the benchmark as both portfolios would achieve similar risk profiles over the investment horizon. This approach to setting the applied leverage allowed for the completion of the third research question

Approach 3 – Volatility-Timing-Levered

This approach treated the constant-levered risk parity portfolio as the underlying portfolio. This would allow for a direct comparison with the constant-levered portfolio as well as the 60/40 benchmark. A multiplier, increasing or decreasing the leverage already present in the constant-levered portfolio was calculated at each daily rebalancing based on the prior rolling 20-day standard deviation.

The portfolio leverage was defined as:

$$k_t = k_{t\ constant-levered} \times \frac{C}{\sigma_{RPcl}}$$

Where

$k_{t\ constant-levered}$ is the constant level of leverage calculated in approach 1

C is a constant

σ_{RPcl} is the rolling 20-day standard deviation of the constant-levered portfolio

The constant was solved for using an excel optimisation function so that the mean standard deviation of the volatility-timing-levered risk parity portfolio matched the mean standard deviation of the 60/40 portfolio. This ensured that, although the exposure of the volatility-timing risk parity portfolio adjusted dynamically, the portfolio achieved the same standard deviation as the benchmark. This presented as taking less risk than the constant-levered portfolio during times of high volatility and taking more risk than the constant-levered portfolio during times of low volatility (Moreira & Muir, 2017). This approach to setting the applied leverage allowed for the completion of the fourth research question

Phase 4 involved completing a time-series of the un-levered risk parity portfolio, with the 3 leverage approaches, and comparing the results to the 60/40 portfolio. While many researchers will compare mean portfolio returns to the benchmark using t-tests to test for significant differences, Ward & Muller (2012) advocate for an alternate approach. Their approach plots the cumulative returns of the portfolios on a graph and then compares the results visually. This approach allows the researcher to visually evaluate how the portfolio performs cumulatively through various market conditions. This approach also allows greater investigation to be done where results differ to what is expected (Ward & Muller, 2012).This approach was utilised to evaluate the relative effectiveness of the RP portfolios in achieving superior returns. This phase allowed for the analysis required to answer the each of the four research questions.

4.8. Limitations

An empirical study of financial data must consider various limitations and assumptions.

4.8.1 Sample period

The sample period, although long, may not be representative of other periods. Risk parity relies heavily on the performance of bonds as they make up the majority of the value of the portfolio. This places risk that the outcome of the investment strategy may be limited by the macroeconomic conditions and business cycles present during the sample period. In the USA the last three decades have been particularly favourable to bonds, given falling interest rates, which has generated flattering real world results for risk parity (Clare, Seaton, Smith, & Thomas, 2016). The external validity of the result is helped by the inclusion of a long sample period however, as business cycles can last decades, as can be seen by a period of 37 years of underperformance by risk parity in a 84 year sample (Anderson et al., 2013), this does represent a limitation to the external validity of the results.

4.8.2 Population definition

The selection of a sample of stocks and bonds from the available population poses a threat to the internal validity of the study due to selection (Saunders et al., 2009) as a large number of JSE listed stocks and bonds were not included in the sample. The sample was performed in line with other researchers methodologies to exclude small and illiquid securities (Ward & Muller, 2012) as these securities may harm the external validity of the results.

4.8.3 Generalisability

An empirical analysis was performed on the JSE, the results of which may not hold in other markets due to differences in structural considerations. The inclusion of literature that has tested these strategies on global markets does assist in increasing the external validity of the findings however, inferences made from this study should be limited to the JSE itself.

Relying on historical secondary data, this research tested whether certain relationships existed in the past, the findings should be viewed as historical and do not ensure the relationships found will exist into the future.

4.8.4 Volatility

This study used a measure of standard deviation to evaluate the risk involved in different trading scenarios. There may be additional sources of risk, that the portfolios are exposed to, that are not taken into consideration in completing this study. This may mean that although two portfolios may have identical volatility, they may face significantly different levels of real-world risk (Jacobs & Levy, 2012).

4.8.5 Transaction Costs

The application of leverage was achieved through a simulated futures portfolio, where exposures were increased (decreased), not by purchasing the underlying assets, but rather by purchasing (selling) futures contracts on these assets. The transaction costs relating to futures contract execution are significantly less than the 1 percentage point often used as a proxy for trading costs when trading equities (Locke & Venkatesh, 1997). A study performed by Locke and Venkatesh (1997) into the actual costs of futures trading on the Chicago Mercantile Exchange found these costs to range from 0,0004 to 0,033 percent. These costs, although low, were excluded from the study. By excluding transaction costs, daily rebalancing did not negatively affect the performance of the portfolios due to increased trading costs.

To achieve a tradeable solution the impact of transaction costs would need to be determined and may affect an optimal rebalancing period. The transaction costs of rebalancing the 60/40 portfolio were excluded to aid comparability which allowed for daily rebalancing. Daily rebalancing of the 60/40 portfolio would be unlikely due to the increased trading costs associated to equities.

CHAPTER 5 Results

The results that follow were presented in reference to the four main research questions posed in Chapter 3. These questions concerned the following:

- A comparison of the cumulative return of an un-levered risk parity portfolio to a 60 / 40 portfolio benchmark
- A comparison of the cumulative return of a constant-levered risk parity portfolio to a 60 / 40 portfolio benchmark
- A comparison of the cumulative return of a target-levered risk parity portfolio to a 60 / 40 portfolio benchmark
- A comparison of the cumulative return of a volatility-timing-levered risk parity portfolio to a 60 / 40 portfolio benchmark

5.1 Results for Research Question 1

5.1.1 Sample Description

The dataset that was used consisted of daily returns data for two indices. These indices were the JSE All Share Index, which consisted of the 160 largest stocks on the JSE, and the JSE All Bond Index, which comprises the top 20 vanilla bonds from across the full range of maturities, ranked dually by liquidity and market capitalisation. The data included were total return data, incorporating dividends and coupon payments into the daily index movement. The daily return data were available from 31 December 1998 to 30 August 2018.

The un-levered risk parity portfolio was created by utilising volatility measures for both the ALSI and ALBI. A rolling 249-day volatility was selected which resulted in the portfolio beginning on the 29th of December 1999. This allowed for a total investment horizon of 4665 trading days, 224 months or 18 years and 8 months.

A risk parity portfolio was created by using the inverse of the 249-day rolling volatility to determine asset class weight.

Mathematically this presented as:

$$\mathcal{W}_{t,i} = \hat{\sigma}_{t,i}^{-1}$$

Where

$\mathcal{W}_{t,i}$ is the weight of each asset class

$\hat{\sigma}_{t,i}$ is the 249-day rolling volatility of monthly excess returns to $t - 1$

Practically this was achieved using

$$\mathcal{W}_{ALBI} = \frac{\frac{\hat{\sigma}_{ALSI}}{\hat{\sigma}_{ALBI}}}{(1 + \frac{\hat{\sigma}_{ALSI}}{\hat{\sigma}_{ALBI}})}$$

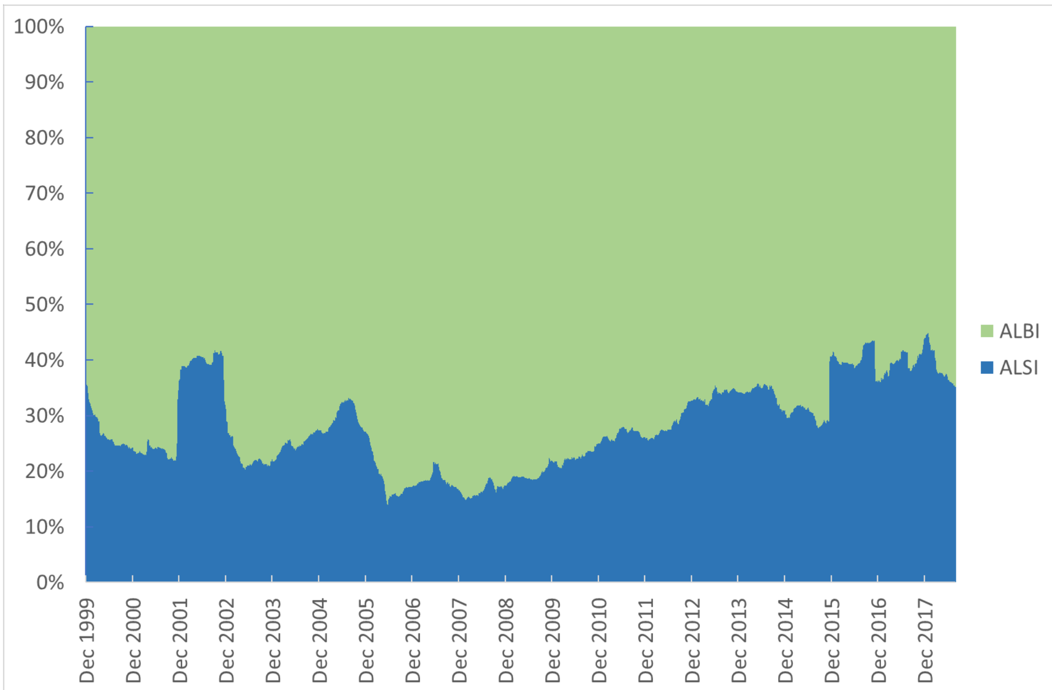
And

$$\mathcal{W}_{ALSI} = 1 - \mathcal{W}_{ALBI}$$

The portfolio weights were rebalanced daily based on the prior volatility. The cumulative performance of this portfolio as well as the benchmark were established by setting portfolio values to 1 on the 29th of December 1999.

Figure 1 indicates the asset class weight of the two underlying portfolios over the investment horizon. This figure provides insight to the relative volatility of the underlying asset classes, as the ALSI becomes relatively more volatile than the ALBI, the ALSI will make up a smaller weight in the risk parity portfolio and vice versa. Over the investment horizon the average portfolio weight of the ALSI was 28,08% showing the higher relative volatility of the ALSI over the ALBI.

Figure1: Risk parity portfolio asset class weights



5.1.2 Comparison of un-levered risk parity with the 60/40 portfolio

To evaluate the un-levered risk parity portfolio, a suitable benchmark was chosen. This was selected as the 60/40 portfolio, which consisted of a portfolio with a 60% weight allocated to the ALSI and a 40% weight allocated to the ALBI, rebalanced daily. The un-levered risk parity portfolio was evaluated on two criteria, namely risk-adjusted performance and cumulative portfolio returns.

5.1.3 Risk comparison of un-levered risk parity with the 60/40

A comparison of the un-levered risk parity portfolio and the 60/40 portfolio was conducted using the Sharpe ratio to obtain a standard measure of risk-adjusted returns. Two versions of the Sharpe ratio were examined, a total return version, referred to as a modified Sharpe ratio, as well as the standard excess return version. The standard version of the Sharpe ratio described in Sharpe (1994) computes excess returns, above a risk-free rate and divides the excess return by the standard deviation. The standard method assumes that funds are borrowed at the risk-free rate to invest in the underlying portfolios and as such, a return in excess of the risk-free rate is used. The risk-free rate quoted below is the mean JIBAR rate, used as a proxy for the risk-free interest rate. The modified version of the Sharpe ratio provides a descriptive measure of total return per unit of standard deviation.

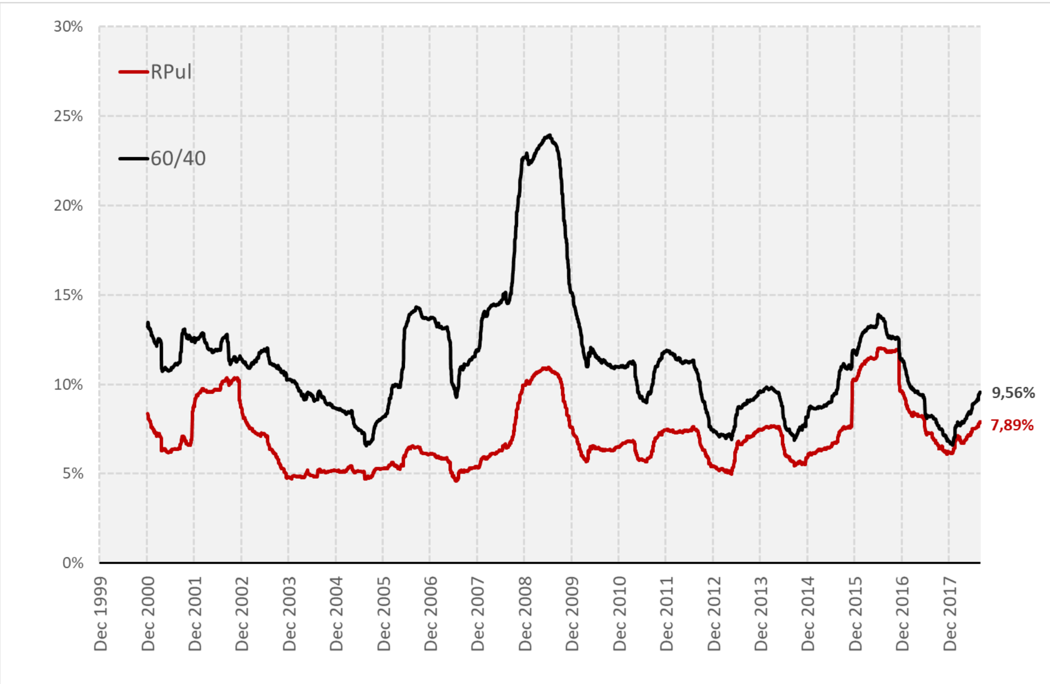
The results are summarised in Table 1. The values below represent annualized figures

Table 1: Sharpe ratio comparison of un-levered risk parity to 60/40

	Un-levered Risk Parity	60/40 Portfolio
Mean Returns	10,86%	12,58%
Standard Deviation	7,42%	11,93%
Mean Risk-Free Rate	8,02%	8,02%
Sharpe Ratio - excess return	0,38	0,38
Modified Sharpe Ratio	1,46	1,05

A time-series of the standard deviations of the un-levered risk parity portfolio and the 60/40 portfolio is presented in Figure 2. This time-series shows the rolling 249-day volatility of the returns of the two portfolios. This time-series allows for a graphical evaluation of how each of the portfolios reacted during differing market conditions.

Figure2: Rolling 249-day Standard Deviation of risk parity un-levered and 60/40 portfolio



5.1.4 Cumulative return comparison of un-levered risk parity with the 60/40

While it may be common practise in literature to evaluate portfolio performance using median returns and applying statistical tests to determine significance, this method may not reflect the effect that exceptionally large gains or losses may have on the actual financial position of an investor's portfolio. Instead, a graphical time-series analysis will be employed.

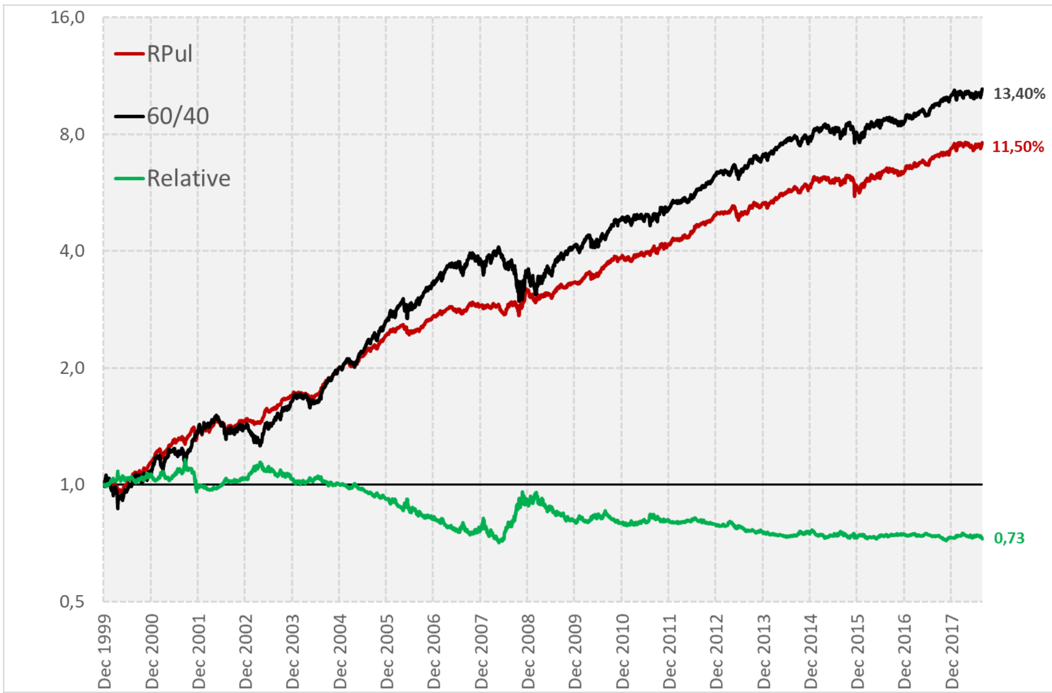
The graphical time-series approach allows for a more powerful examination of the differences in portfolio performance over time. This visual approach allows for patterns to emerge showing the size and duration of performance differentials.

The return measure denoted in the hypothesis used to compare un-levered risk parity to the 60/40 portfolio refers to cumulative returns over the entire investment period. It is important to note that while a hypothesis is used, a graphical time-series does not allow for statistical acceptance or rejection of the hypothesis.

$$H_{1^{0}} : R_{RPul} - R_{60/40} = 0$$
$$H_{1^{A}} : R_{RPul} - R_{60/40} <> 0$$

The graphical time-series presented in Figure 3 was constructed using the cumulative returns of the un-levered risk parity portfolio and the 60/40 portfolio, starting from a base of 1. A relative return curve was included to show the relative performance of the un-levered risk parity portfolio in relation to the 60/40 portfolio. This was constructed by dividing the cumulative returns of the un-levered risk parity portfolio by the cumulative returns of the 60/40 portfolio. This curve will show periods of outperformance (underperformance) by the un-levered risk parity as a positive (negative) slope with the angle and duration of the slope denoting the severity of the differences in performance. The compound annual growth rates (CAGR) are displayed on the right of the graph.

Figure 3: Cumulative returns of risk parity un-levered and 60/40 portfolio



5.2 Results for research question 2

5.2.1 Sample Description

In addressing question two, leverage was then applied to the un-levered risk parity portfolio. This was conducted at a portfolio level rather than applying leverage to each underlying asset class. This meant that the leverage did not affect the relative weight of the ALSI and ALBI in the risk parity portfolio. The leverage was achieved by simulating the mechanics of a portfolio that relied on futures to gain exposure to the two indices.

An initial portfolio value of R100 was selected. This was invested to achieve a risk-free cash return. The ALSI and ABLI exposure was made up entirely of simulated futures that incorporated the risk-free rate as a cost of borrowing. The JIBAR rate was selected as a reasonable proxy for the risk-free rate of investment and borrowing.

A constant level of leverage was computed so that the standard deviation of the risk parity portfolio matched the ex-post standard deviation of the 60/40 portfolio. The portfolio was rebalanced daily to ensure the level of leverage remained constant throughout the investment window. The computed leverage required to match the mean standard deviation of the risk parity portfolio to the 60/40 portfolio was 1,61 times.

5.2.2 Risk comparison of constant-levered risk parity with the 60/40

A comparison of the constant-levered risk parity and the 60/40 portfolios was conducted using the Sharpe ratio to obtain a standard measure of risk-adjusted returns.

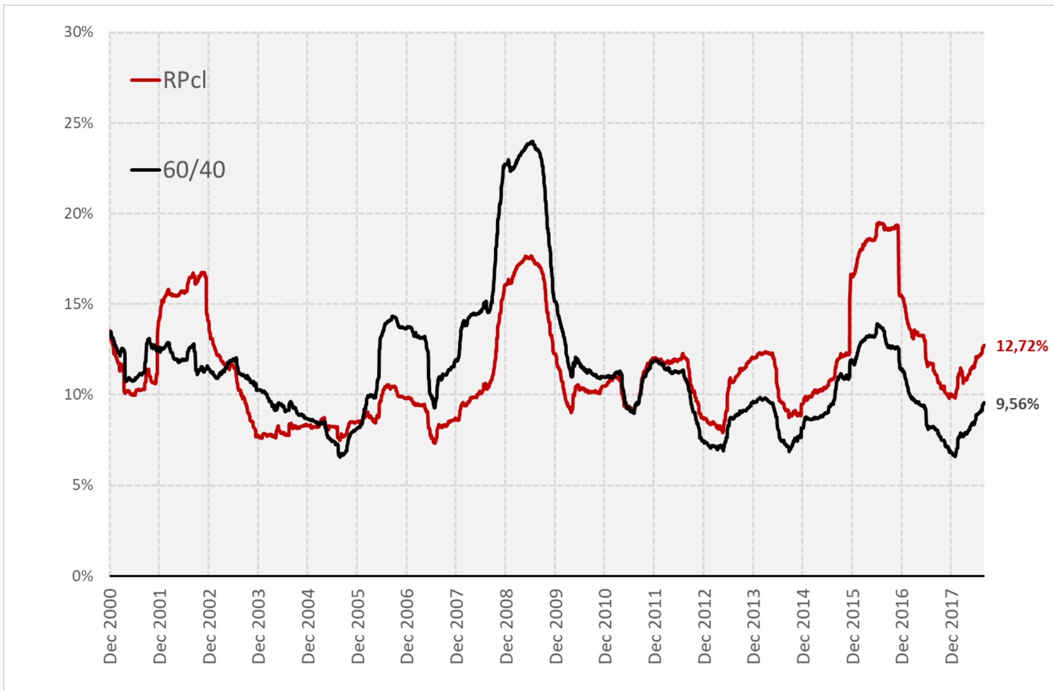
The results are summarised in Table 2. The values below represent annualized figures

Table 2: Sharpe ratio comparison of constant-levered risk parity with 60/40

	Constant-levered Risk Parity	60/40 Portfolio
Mean Returns	12,31%	12,58%
Standard Deviation	11,93%	11,93%
Mean Risk-Free Rate	8,03%	8,03%
Sharpe Ratio - excess return	0,36	0,38
Modified Sharpe Ratio	1,03	1,05

A time-series of the standard deviations of the constant-levered risk parity portfolio and the 60/40 portfolio is presented in Figure 4. This time series shows the rolling 249-day volatility.

Figure 4: Rolling 249-day Standard Deviation of risk parity constant-levered and 60/40 portfolio



5.2.3 Cumulative return comparison of constant-levered risk parity with the 60/40

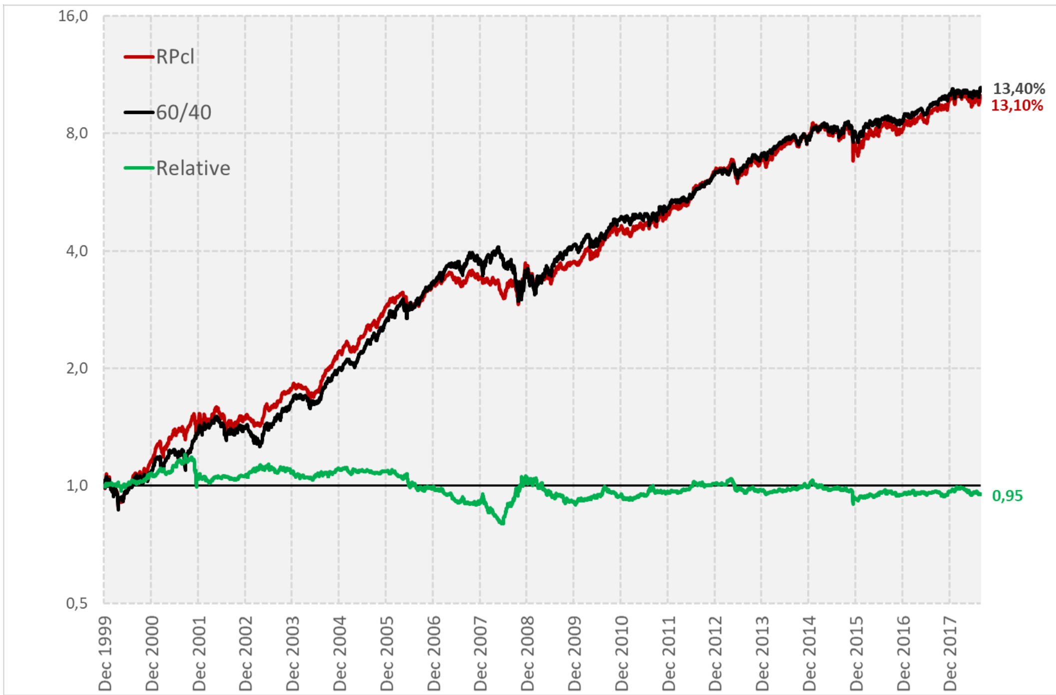
A graphical time-series was chosen to evaluate the cumulative returns of a constant-levered risk parity portfolio with a 60/40 portfolio. The hypothesis for this test was denoted as:

$$H_{2^0} : R_{RPcl} - R_{60/40} = 0$$

$$H_{1^A} : R_{RPcl} - R_{60/40} <> 0$$

The graphical time-series presented in Figure 5 was constructed using the cumulative returns of the constant-levered risk parity portfolio and the 60/40 portfolio, starting from a base of 1. A relative return curve was included to show the relative performance of the constant-levered risk parity portfolio in relation to the 60/40 portfolio. The CAGR’s are displayed on the right of the graph.

Figure 5: Cumulative returns of risk parity constant-levered and 60/40 portfolio



5.3 Results for research question 3

5.3.1 Sample Description

In addressing question three, leverage was applied to the un-levered risk parity portfolio. This was conducted at a portfolio level rather than applying leverage to each underlying asset class. This meant that the leverage did not affect the relative weight of the ALSI and ALBI in the risk parity portfolio.

An initial portfolio value of R100 was selected. This was invested to achieve a risk-free cash return. The ALSI and ABLI exposure was made up entirely of simulated futures that incorporated the risk-free rate as a cost of borrowing. The JIBAR rate was selected as a reasonable proxy for the risk-free rate of investment and borrowing.

The targeted-standard deviation method attempted to match the standard deviation in the risk parity portfolio to the standard deviation of the 60/40 by dynamically adjusting the amount of leverage applied to the un-levered risk parity portfolio. The risk parity portfolio standard deviation matched the ex-post standard deviation of the 60/40 portfolio over the entire portfolio horizon.

As the leverage was being dynamically applied without a look-ahead scenario, the two standard deviations do diverge at times. The portfolio was rebalanced daily to track as closely to the target standard deviation of the 60/40 portfolio

5.3.2 Risk comparison of target-levered risk parity with the 60/40

A comparison of target-levered risk parity and the 60/40 portfolio was conducted using the Sharpe ratio to obtain a standard measure of risk-adjusted returns.

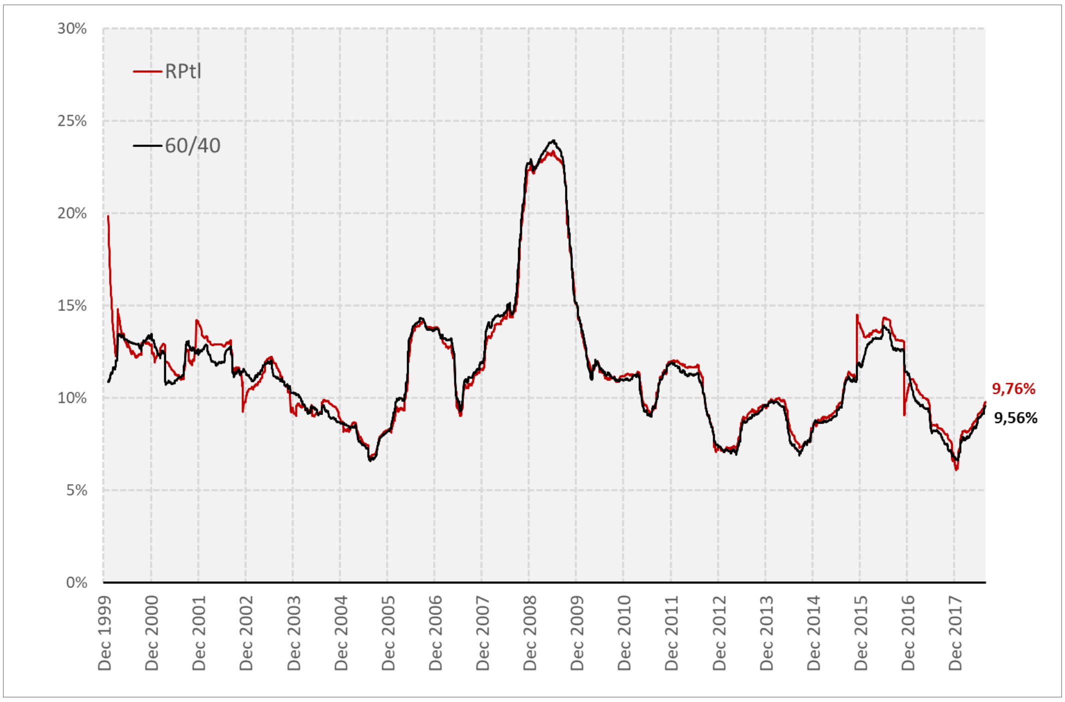
The results are summarised in Table 3. The values below represent annualized figures

Table 3: Sharpe ratio comparison of Target-levered risk parity to 60/40

	Target-levered Risk Parity	60/40 Portfolio
Mean Returns	12,34%	12,58%
Standard Deviation	11,93%	11,93%
Mean Risk-Free Rate	8,03%	8,03%
Sharpe Ratio - excess return	0,36	0,38
Modified Sharpe Ratio	1,03	1,05

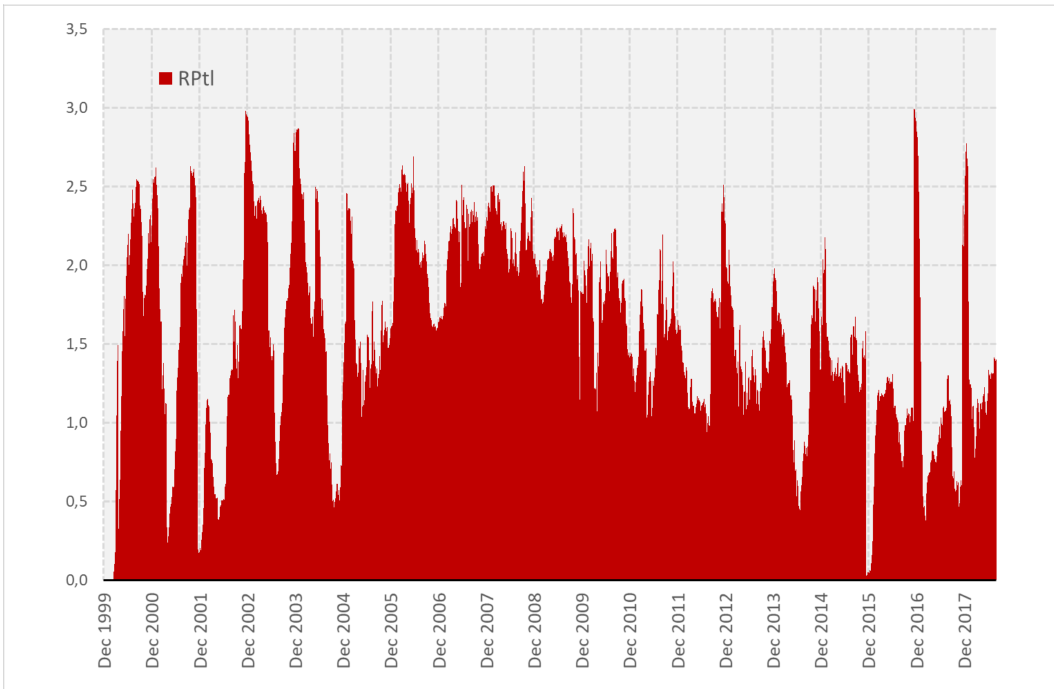
A time-series of the standard deviations of the target-levered risk parity portfolio and the 60/40 portfolio is presented in Figure 6. This time series shows the rolling 249-day volatility.

Figure 6: Rolling 249-day Standard Deviation of risk parity Target-levered and 60/40 portfolio



The dynamic quantity of leverage required to match the standard deviation of the 60/40 portfolio was plotted on a time-series to provide graphical insight. The time series is presented in Figure 7.

Figure 7: Amount of leverage applied to the Target-levered risk parity portfolio



5.3.3 Cumulative return comparison of target-levered risk parity with the 60/40

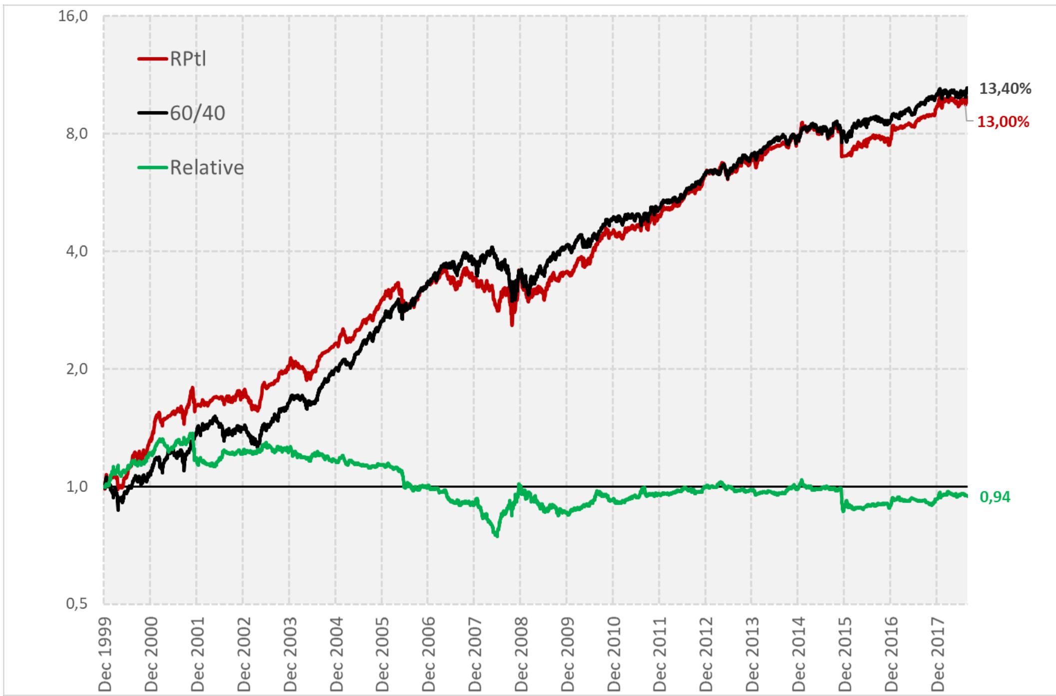
A graphical time-series was chosen to evaluate the cumulative returns of a target-levered risk parity portfolio with a 60/40 portfolio. The hypothesis for this test was denoted as:

H_{3^0} : R_{RPtl} - $R_{60/40}$ = 0

H_{3^A} : R_{RPtl} - $R_{60/40}$ <> 0

The graphical time-series presented in Figure 8 was constructed using the cumulative returns of the target-levered risk parity portfolio and the 60/40 portfolio, starting from a base of 1. A relative return curve was included to show the relative performance of the target-levered risk parity portfolio in relation to the 60/40 portfolio. The CAGR's are displayed on the right of the graph

Figure 8: Cumulative returns of risk parity target-levered and 60/40 portfolio



5.4 Results for research question 4

5.4.1 Sample Description

In addressing question four, leverage was applied to the un-levered risk parity portfolio. This was conducted at a portfolio level rather than applying leverage to each underlying asset class. This meant that the leverage did not affect the relative weight of the ALSI and ALBI in the risk parity portfolio.

An initial portfolio value of R100 was selected. This was invested to achieve a risk-free cash return. The ALSI and ABLI exposure was made up entirely of simulated futures that incorporated the risk-free rate as a cost of borrowing. The JIBAR rate was selected as a reasonable proxy for the risk-free rate of investment and borrowing.

The volatility-timed-standard deviation method attempted to dynamically adjust the amount of leverage applied based on the inverse of the preceding 20 days volatility. This applied more (less) leverage when volatility was low (high). The risk parity portfolio standard deviation matched the ex-post standard deviation of the 60/40 portfolio over the entire portfolio window. The portfolio was rebalanced daily to track as closely to the target standard deviation of the 60/40 portfolio

5.4.2 Risk comparison of volatility timing-levered risk parity with the 60/40

A comparison of volatility-timing-levered risk parity and the 60/40 portfolio was conducted using the Sharpe ratio to obtain a standard measure of risk-adjusted returns.

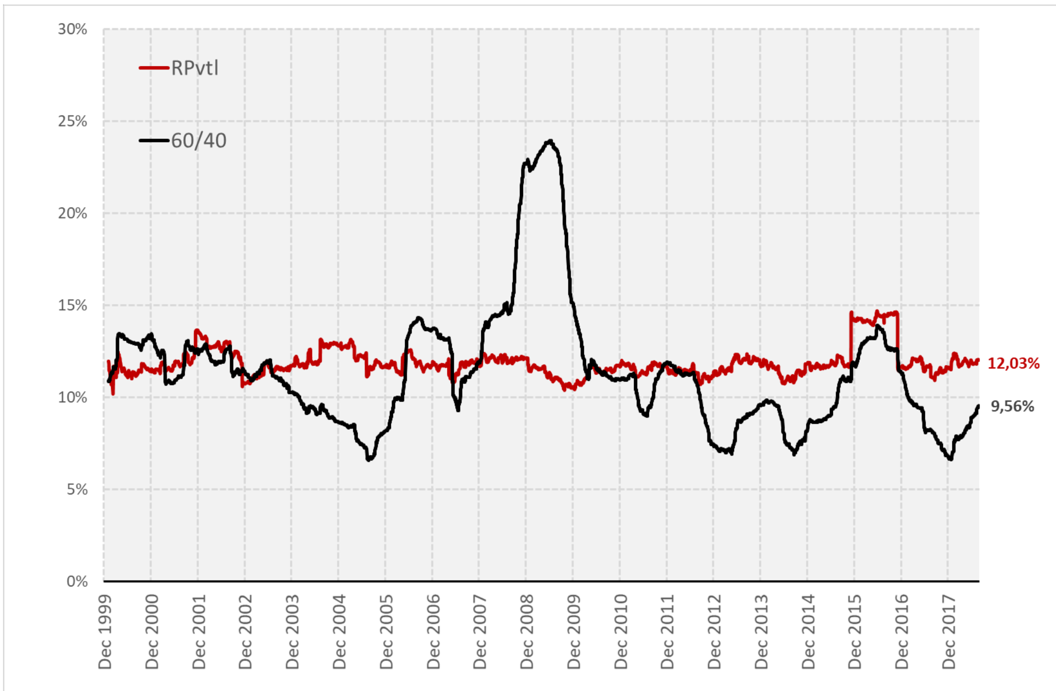
The results are summarised in Table 4. The values below represent annualized figures

Table 4: Sharpe ratio comparison of Volatility-timing-levered risk parity to 60/40

	Volatility-timing-levered Risk Parity	60/40 Portfolio
Mean Returns	12,13%	12,58%
Standard Deviation	11,93%	11,93%
Mean Risk-Free Rate	8,03%	8,03%
Sharpe Ratio - excess return	0,34	0,38
Modified Sharpe Ratio	1,02	1,05

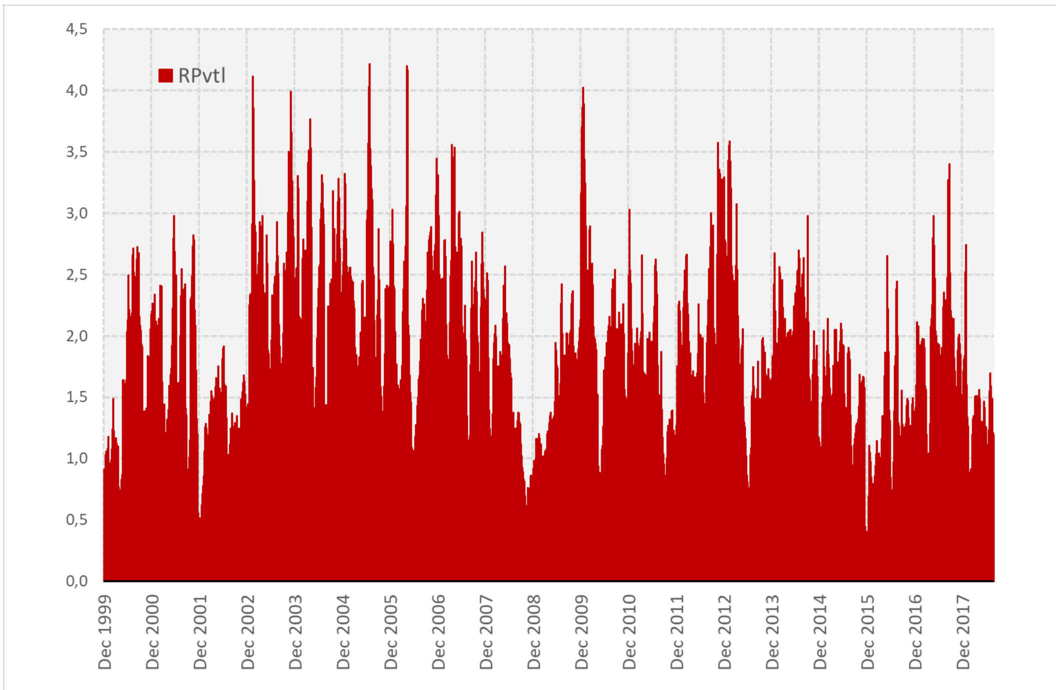
A time-series of the standard deviations of the volatility-timing-levered risk parity portfolio and the 60/40 portfolio is presented in Figure 9. This time series shows the rolling 249-day volatility.

Figure 9: Rolling 249-day Standard Deviation of risk parity Volatility-timing-levered and 60/40 portfolio



The dynamic quantity of leverage, based on realised 20 day volatility, was plotted on a time-series to provide graphical insight. The time series is presented in Figure 10.

Figure 10: Amount of leverage applied to the Volatility-timing-levered risk parity portfolio



5.4.3 Cumulative return comparison of Volatility-timing-levered risk parity with the 60/40

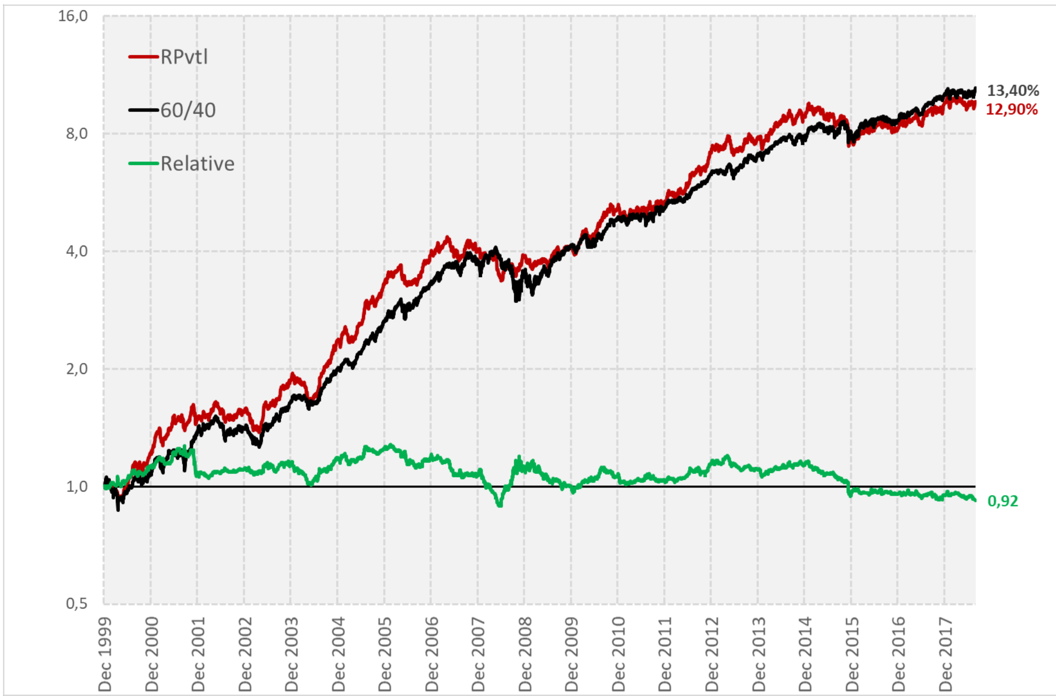
A graphical time-series was chosen to evaluate the cumulative returns of the volatility-timing-levered risk parity portfolio with a 60/40 portfolio. The hypothesis for this test was denoted as:

$$H_{4^0} : R_{RPvl} - R_{60/40} = 0$$

$$H_{4^A} : R_{RPvl} - R_{60/40} <> 0$$

The graphical time-series presented in Figure 8 was constructed using the cumulative returns of the target-levered risk parity portfolio and the 60/40 portfolio, starting from a base of 1. A relative return curve was included to show the relative performance of the volatility-timing-levered risk parity portfolio in relation to the 60/40 portfolio. The CAGR's are displayed on the right of the graph

Figure 11: Cumulative returns of risk parity volatility-timing-levered and 60/40 portfolio



CHAPTER 6 Discussion of results

The results presented in chapter 5 will be discussed further below. A risk parity portfolio was successfully created using a simple inverse of asset class volatility. This unlevered portfolio presented potential for further examination with a modified Sharpe ratio higher than that of the 60/40 portfolio. Leverage was applied in three different methods however none of the methods produced a portfolio that was able to provide a greater cumulative return than the 60/40 portfolio over the investment horizon for the same amount of risk. This suggests that risk parity is not able to exploit and market inefficiencies that may exist outside of the efficient market hypothesis (Fama, 1970).

6.1. Discussion regarding research question 1

Research question one explored the un-levered risk parity portfolio as a viable asset allocation technique on the JSE over the last 18 years when compared to a popular benchmark, the 60/40 portfolio.

Firstly, the un-levered risk parity portfolio was created based on the rolling 249-day volatility of the ALSI and ABLI. This portfolio was found to produce a greater level of total return per unit of risk. The results were compared using a number of alternative methods, to evaluate total return and risk adjusted return.

Although the 60/40 portfolio showed a greater total return, the risk parity portfolio achieved a lower level of risk. To evaluate the risk parity portfolio, measures of risk-adjusted performance were necessary, together with an examination into significant market movements that occurred over the investment horizon.

6.1.1 Risk characteristics of the un-levered risk parity portfolio

The volatility of the underlying asset classes were the only inputs into calculation their respective weights in the risk parity portfolio. Volatility refers to the fluctuations in returns that the asset class experiences. Volatility has been shown to be a critical component in portfolio construction and managing portfolio risk (Fleming et al., 2001). Daily weights were calculated based on the return variations of the prior 249 trading days.

When examining the asset class weights over time in figure 1 we can see that the portfolio had a general trend towards a greater percentage of bonds in the portfolio that stocks (Asness et al., 2012). This was not, however, a consistent trait of the risk parity portfolio as the portfolio sought to balance volatility rather than favour bonds over stocks (Bai et al., 2016). Over the investment period the average weight of the ALSI in the risk parity portfolio was 28,02 percent. This is similar to prior studies conducted in international markets by Asness et al. (2012) where they found their average weight of equities was 15 percent.

The lower comparative percentage of bonds in the risk parity portfolio than in the study conducted by Asness et al. (2012) highlights a possible structural difference in the South African financial markets when compared to that of the USA. This may be attributed to the constituents of the bond index, with a larger portion of higher rated bonds in the USA bond index used by Asness et al. (2012) than the ALBI. This may have resulted in a diluted effect of risk parity in the South African market as the strategy relies on the availability of low beta assets (Clarke et al., 2013).

Over the investment horizon, the average standard deviation of the ALSI was 17,96 percent while the ALBI was 6,88 percent. When examining a 60/40 portfolio in South Africa it can be seen that, similar to international markets, the risk present in the 60 percent of equities dominates the total risk exposure of the portfolio (Qian, 2011).

The risk parity portfolio incorporates a measure of risk management by dynamically changing portfolio make-up through market anomalies. The investment horizon includes three broad market anomalies incorporated in it, the dot-com bubble in the early 2000’s, the financial crisis in 2008 and the Nene-gate scandal at the end of 2015. The first two events were global events that also effected the JSE, the third event was a South African event, when the president removed the finance minister from office.

The portfolio weightings react dynamically to these events, balancing risk weightings to be less exposed to high relative volatility. The high volatility is not only high equity volatility but also high bond volatility evident at the end of 2015. At the height of the financial crises the risk parity portfolio had an exposure to the ALSI of only 13,93 percent.

This dynamic allocation together with a low exposure to stocks on average meant that the risk parity portfolio achieved a standard deviation of 7,42 percent compared to a standard deviation of 11,93 percent for the 60/40 portfolio.

Examining standard deviation over time in Figure 2, it is evident that the risk parity portfolio was consistently lower in volatility than the 60/40 portfolio. With the greatest difference experienced between 2008 and 2010. During this period, the 60/40 investor would have achieved a much greater variation in returns with standard deviations far exceeding the long run average. The risk parity portfolio also experienced a greater standard deviation during this period however the standard deviation remained within the ambit of long-term averages. This can be attributed to the inherent risk management present in a risk parity portfolio.

The relative distance between the standard deviation of the risk parity portfolio and the 60/40 portfolio has been decreasing since 2012, with the period from 2013 through to the end of the window exhibiting a very similar level of portfolio standard deviation. This time period has also shown an increase in the weighting of the ALSI in the risk parity portfolio showing a decrease in the relative volatility of the ALSI to the ALBI. This weight rebalancing exhibits similar characteristics as those described in the volatility-timing methodology, albeit on a longer timescale, of increasing exposure during times of low relative volatility to capture the greater mean-variance profile of the ALSI asset class during this period (Moreira & Muir, 2017).

6.1.2 Return characteristics of the un-levered risk parity portfolio

The returns of the un-levered risk parity portfolio were presented. Although a lower risk profile was achieved, this must be weighed up relative to the returns that the portfolio achieved as risk reduction is not the primary aim of portfolio creation but is an enabler to achieve superior returns (Lee, 2011). The returns achieved will be discussed on two characteristics, on a risk adjusted basis and on a cumulative return basis.

The un-levered risk parity portfolio achieved a mean return of 10,86 percent over the 18-year investment window. This is in contrast to a 12,58 percent mean return for the 60/40 portfolio. Although the mean return was below that of the 60/40 portfolio, the standard deviation was also below that of the 60/40 with 7,42 percent to the 11,93 percent of the 60/40. To gain insight into the relative attractiveness of these returns, they will be examined using the Sharpe ratio as a measure of risk-adjusted performance.

The modified Sharpe ratio, comparing total mean return to mean standard deviation, we can see comparative outperformance by the risk parity portfolio, with a modified Sharpe ratio of 1,46 to the 1,05 of the 60/40. This is interpreted such that for one unit of standard deviation, the risk parity portfolio provides 1,46 times the return. Sharpe (1994) argues that while this measure may be useful as a descriptive statistic, it lacks the properties for the direct comparison of portfolios when an investor has the option to combine the risky portfolio with some proportion of the risk-free asset.

When the risk parity portfolio is compared to the 60/40 portfolio using the standard Sharpe ratio, both portfolios achieve the same Sharpe ratio of 0,38. This is interpreted such that both portfolios provide 0,38 units of return, in excess of the risk-free rate, for each unit of standard deviation. This is important as it predicts that the same return as the risk parity portfolio could be had by the 60/40 portfolio if it was combined with the risk-free asset in a proportion that produced the same standard deviation. This is key to the study as the risk parity portfolio is assumed to need leverage, equivalent to shorting the risk-free asset, in order to achieve a high enough total return.

By achieving the same Sharpe ratio in both portfolios, it suggests that the market inefficiencies identified by Asness et al (2012) are not present during the time horizon of the study on the JSE. Prior research found an excess return premium on low risk assets which was attributed to a mispricing due to leverage aversion (Asness et al., 2012). This premium on low risk assets was also identified by Frazzini and Pederson (2014) which if evident in the two indexes used, would have provided some measure of outperformance by the risk parity portoflio. This was not seen in the test conducted.

A difference in the Sharpe ratios would have identified a market inefficiency, however with the same Sharpe ratio this would indicate the market was efficient at pricing the risk premium on stocks and bonds in aggregate over this time period (Fama, 1970).

This is not to say that there were not periods of relative risk-adjusted outperformance by either the ALSI or ALBI within the investment period, rather that when taken on aggregate this was not the case. This may highlight a sensitivity of the risk parity result to the time horizon studied. This concern was raised by Chaves et al. (2011) when their study found a very marginal difference in the Sharpe ratio of the risk parity portfolio and the 60/40 benchmark.

In light of the Sharpe ratio result, concerns around the number of competing methods to create parity in risk should not be seen to be material (Clarke et al., 2013). While optimisation of the weightings may have changed the result marginally, the simple inverse of prior volatility was successful in substantially increasing the exposure to the low risk asset compared to the 60/40 portfolio. If a risk-adjusted return premium on the low risk asset, caused by market inefficiencies, was present, the simple weighting technique should have highlighted it with greater risk-adjusted returns.

When examining the cumulative returns of the un-levered risk parity portfolio presented in Figure 3, the graphical time series allows for patterns to emerge. It is clear that over the investment window, the risk parity portfolio underperforms the 60/40 portfolio on a total return basis, achieving 73 percent of the portfolio value of the 60/40. Within the period however, there are significant periods of outperformance.

Within the first 5-year period from December 1999 to December 2004, the risk parity portfolio had spent much of this time outperforming the 60/40 portfolio in terms of cumulative return, all with a lower standard deviation. This period experienced a number of difficult periods for the 60/40 portfolio where the risk parity, with its lower exposure to equities, experienced less severe drawdowns.

The equities bull run leading up to the financial crisis was a significant period of outperformance for the 60/40 portfolio. The relative measure showed a persistent negative slope indicating returns outperformance by the 60/40 portfolio. This period was characterised within the risk parity portfolio by declining weights of equities and a persistently low level of portfolio standard deviation.

The financial crisis that occurred throughout 2008 and into 2009 provided market conditions that significantly favoured the risk parity portfolio. The cumulative returns line shows a mild flattening during this period, contrasted by a significant drawdown experienced by the 60/40 portfolio. This drawdown in the 60/40 portfolio erased much of the cumulative gains that had been experienced in the bull run leading up to the crisis. This highlights the asymmetry experienced in cumulative portfolio values when portfolios experience gains and losses. By March 2009, almost 10 years after the starting point, the risk parity portfolio was at 96 percent of the value of the 60/40 portfolio, all achieved with significantly less standard deviation.

The last ten years of the investment window were far less turbulent. This period saw a slow but consistent decline in the relative cumulative returns of the risk parity portfolio. As the risk parity portfolio saw a steady increase in the equities weighting, the two portfolios acted more alike. The market turbulence at the end of 2015 was as a result of the Nene-gate scandal which effected both equities and bonds negatively, leaving the relative difference between the risk parity portfolio and the 60/40 largely unchanged.

In assessing the attractiveness of the un-levered risk parity portfolio to an investor, it would provide a relatively smoother performance, loosing relative value during periods of strong equity performance but providing some level of shielding from equity market downturns. The cumulative performance was however not greater or worse than would be expected for the risk level of the portfolio. While periods of outperformance were experienced these were not persistent and as such may be difficult to exploit consistently by the investor.

6.2. Discussion regarding research question 2

Question two explored the effects of applying leverage to the un-levered risk parity portfolio. To achieve this, a constant level of leverage was applied to the portfolio, rebalanced daily, so that the standard deviation of the constant-levered risk parity portfolio matched the realised standard deviation of the 60/40 portfolio.

This level of leverage would not have been known at the start of the investment and as such does not represent an investible solution. A more likely scenario of the real-world application of this form of leverage would involve the investor selecting a level of leverage that they were comfortable with, or could sustain, and applying this consistently throughout the holding period. In order to aid the comparability of the constant-levered risk parity portfolio with the 60/40 portfolio, a computed leverage of 1,61 times was applied throughout the investment window.

Leverage was achieved through a simulated futures portfolio (Asness et al., 2012). The cost of leverage applied throughout the investment window was the JIBAR rate. This was chosen as a proxy for the risk-free rate and would be the futures contracts provider’s cost of capital. At a constant gearing of 1,61 times, the investor would be paying the JIBAR rate on 1,61 times the portfolio value and receiving JIBAR on 1 times the portfolio value. This is in line with the CAPM assumptions that investors are able to borrow and lend at the risk free rate (Fama & French, 2004).

6.2.1 Risk characteristics of the constant-levered risk parity portfolio

The leverage was selected to equalise the standard deviation of the constant-levered risk parity portfolio to the 60/40 portfolio as can be seen in Table 2. The mean return achieved was below that of the 60/40 portfolio which has negatively affected the Sharpe ratio, although marginally at 0,36 compared to 0,38. This lower Sharpe ratio would indicate that an investor would maximise their utility by selecting the 60/40 portfolio over the constant-levered risk parity portfolio.

The time-series of the standard deviations is presented in Figure 4. As the mean standard deviations match, areas where the 60/40 is higher than the constant-levered risk parity portfolio are matched by the inverse in other periods. For much of the time until 2010, the constant-levered risk parity portfolio had a lower standard deviation than the 60/40 portfolio. There appeared to be a structural shift that occurred in 2010, after which the standard deviation of the constant-levered risk parity portfolio was consistently above that of the 60/40 portfolio. The high levered exposure to bonds proved to be detrimental to portfolio volatility at the end of 2015 when bonds were negatively affected by adverse market conditions.

6.2.2 Return characteristics of the constant-levered risk parity portfolio

The constant-levered risk parity portfolio achieved a mean return of 12,31 percent compared to the 12,58 percent of the 60/40 portfolio. This resulted in a cumulative portfolio value that was 95 percent of the value of the 60/40 portfolio.

Interestingly, although the constant-levered risk parity portfolio had 1,61 times the exposure of the un-levered risk parity portfolio, it was only able to achieve an additional 1,45 percent of mean return, an increase of 1,1 times over the un-levered portfolio. This highlights the cost of leverage and its effects on performance. This provides evidence that the Sharpe ratio is better suited to evaluating competing portfolios than the modified Sharpe ratio using total return when portfolios will be combined with the risk-free asset (Sharpe, 1994).

The relative performance line in Figure 5 provides a similar shape to the un-levered risk parity performance, levering periods of outperformance but also levering periods of underperformance. The constant-levered risk parity portfolio was consistently ahead of the 60/40 portfolio for the first seven years of the investment window. The risk parity portfolio lost its greatest share of relative performance in the two years before the financial crisis but performed well through the crisis. The relative graph remained largely flat through to 2015 where the poor bond performance effected the risk parity portfolio with its large levered bond exposure.

The constant-levered risk parity portfolio did show periods of out-performance; however, these periods were not consistent and would be difficult to invest in such a way as to capture them.

Providing constant leverage to a risk parity portfolio did not produce any excess returns and would not present as a more attractive alternative to the 60/40 portfolio (Chaves et al., 2011).

6.3. Discussion regarding research question 3

Question three explored applying leverage to the un-levered risk parity portfolio, as in question two, however the leverage was applied in a targeted manner. The realised volatility of the 60/40 portfolio was the target so that the leverage applied to the risk parity portfolio would adjust daily to achieve a rolling 249-day standard deviation that matched the target. The mean standard deviation of the investment horizon was matched so that both the target-levered risk parity portfolio and the 60/40 portfolio achieved the same mean standard deviation.

A sigmoid function was used to determine the leverage at each daily rebalancing point. The function sought to minimise the difference between the standard deviation of the target-levered risk parity portfolio and the 60/40 portfolio. The sigmoid function was optimised using the entire portfolio which makes this level of accuracy unlikely in a real-world application, however the function would evolve over time to plausibly achieve similar results.

This method of applying leverage is a solution to the observed differing levels of standard deviation during different market structures with constant leverage. While the constant-levered risk parity was comparatively less volatile up to 2010 and more volatile after 2010 this method matched the standard deviation throughout the investment horizon.

The amount of leverage applied is presented in Figure 7. The leverage ranged from a minimum of zero, where no market exposure was achieved with only the cash portion receiving a risk-free return up to three times. The level of leverage changed dramatically as each month an estimation of the leverage required would be made. This estimate would need to be adjusted each month when realised volatility either proved the estimate correct or incorrect.

6.3.1 Risk characteristics of the target-levered risk parity portfolio

The mean return and standard deviation data for the target-levered risk parity portfolio

Can be found in Table 3. The mean return achieved by the target-levered risk parity portfolio was 12,34 percent. This was 0,03 percent higher than the constant-levered risk parity portfolio. The marginal change did not meaningfully affect the Sharpe ratio achieved by the target-levered risk parity portfolio. This lower Sharpe ratio than the 60/40 portfolio indicates that an investor would not maximise utility by selecting this portfolio over the 60/40 portfolio.

Examining the time series of realised standard deviation, the optimisation can be seen to be tracking the standard deviation of the 60/40 portfolio although shock events such as in December 2015 do cause a deviation.

When compared to the constant-levered risk parity portfolio, this targeted approach has resulted in the risk parity portfolio taking substantially more risk during the 2008 financial crisis than the constant-levered portfolio. As the volatility of the benchmark, and by implication the market, increases, the risk parity portfolio will increase its exposure to match the increased volatility.

6.3.2 Return characteristics of the target-levered risk parity portfolio

The target-levered risk parity portfolio achieved a mean return of 12,34 percent compared to the 12,58 percent of the 60/40 portfolio. This resulted in a cumulative portfolio value that was 96 percent of the value of the 60/40 portfolio.

When examining the cumulative returns in Figure 8 it can be seen that this method of leverage resulted in a greater outperformance in the first six years of the investment than any other method of applying leverage. At its greatest relative level, the target-levered risk parity portfolio’s cumulative value was 37 percent greater than the 60/40 portfolio and this was achieved after only two years. The relative outperformance was not sustained, with subsequent losses erasing any cumulative gains such that the relative performance was flat up until 2015.

As with constant-leverage, although there are periods of outperformance, these soon reverse and appear to be a symptom of the leverage strategy performing better in some market structures than others, rather than an optimal leverage strategy that is able to capture gains.

6.4. Discussion regarding research question 4

Question 4 examined a dynamic method of applying leverage to the un-levered risk parity portfolio. This method was designed to test a market timing strategy that had shown to produce excess risk adjusted returns when applied to a number of underlying portfolios but had not been applied to an underlying risk parity portfolio.

The volatility-timed method would increase (decrease) exposure when a decrease (increase) in the rolling 20-day volatility of the underlying portfolio occurred. A constant was computed such that the mean standard deviation of the volatility-timing-levered risk parity portfolio matched the mean standard deviation of the 60/40 portfolio.

This method is an investible solution as adjustments to leverage are made based off of the prior realised volatility. The prior 20 days volatility is taken as a proxy for the next single day's volatility. This method relies on the relationship of prior volatility to future volatility holding constant (Moreira & Muir, 2017). The constant that was responsible for setting the portfolio long standard deviation was computed using the entire investment window to provide greater comparability with the 60/40 portfolio. In an investible solution, this constant may change over time based on underlying market conditions and desired risk exposure.

Figure 10 displays a time series of the amount of leverage applied at each daily rebalancing. The leverage ranges from 0,39 times up to 4,24 times with an average leverage of 1,81 times. The lowest levels of leverage can be seen coinciding with the previously identified market events in 2001, 2008 and 2015. As volatility increases during these turbulent times, the low levels of leverage reduce the exposure of the portfolio to these movements. Although the leverage is adjusted based on short term volatility, this method is in direct contrast with the standard deviation targeted method which would increase leverage to match the increased volatility experienced by the 60/40 portfolio.

6.4.1 Risk characteristics of the volatility-timing-levered risk parity portfolio

The volatility-timing-levered risk parity portfolio achieved the lowest mean return of all of the levered portfolios with a return of 12,13 percent. This caused the Sharpe ratio to drop to 0,34 compared to the 0,38 of the 60/40 portfolio.

When examining the time-series of the 249-day rolling standard deviation of the volatility-timing-levered risk parity portfolio it can be seen that an unintended consequence of the volatility timing methodology has resulted in a standard deviation that is relatively flat over the investment window. This may provide evidence that the rolling 20-day volatility is generally a good predictor of the next one-day volatility (Andersen et al., 2003).

The time series does highlight a particular case in the investment window where this did not hold true. The large spike in volatility in December 2015 shows that a period of very high volatility immediately followed a period of relatively low volatility, such that the portfolio had high leverage applied to it as the news of Nhlanhla Nene's firing was announced. This high volatility period is held throughout the next 249-days of the standard deviation figures. However, it only affected the leverage calculation for the next 20-days due to the differing methodology.

As an investible strategy, the relatively stable standard deviation does provide an easier experience for the investor, especially one with strict risk budgets to adhere to over time.

6.4.2 Return characteristics of the volatility-timing-levered risk parity portfolio

The volatility-timing-levered risk parity portfolio achieved a mean return of 12,13 percent compared to the 12,58 percent achieved by the 60/40 portfolio. This relative underperformance resulted in a final portfolio value that was 92 percent of the value of the 60/40 portfolio.

When examining the cumulative returns of the volatility-timing-levered risk parity portfolio presented in Figure 11 it can be seen that the risk parity portfolio spent much of the 18-year investment window with the relative measure above 1. Had the study ended in 2014, the return characteristics would have appeared to support a strategy based on volatility timing. It would appear that as a general case a strategy that exploits volatility's short-term predictability is more persistent that the two alternate methods of applying leverage that have been tested.

However, in the specific case presented in the investment window of this strategy, this strategy resulted in the lowest cumulative return of any leveraged strategy.

The 10th of December 2015 presents an example where dramatic news reached the market in a single day. Within the next two days, the volatility-timing-levered risk parity portfolio had lost around 10 percent of its value. The rolling 20-day volatility did not predict the high volatility that was about to occur. This highlights the danger of assuming that volatility relationships will exist consistently over time (Fleming et al., 2001).

The relative line does not indicate a lasting positive trend, but rather that there are market conditions where the strategy outperformed and conditions where it did not. This would make it difficult to adopt as a long-term strategy for achieving superior returns.

The Sharpe ratio of the un-levered risk parity portfolio indicated that with leverage applied, it would not likely outperform the 60/40 portfolio. This has been found to be true across multiple methods of applying leverage. The ability to time the market volatility and dynamically apply leverage to capture market inefficiencies has not been shown to produce economic value over the investment horizon (Fleming et al., 2001).

CHAPTER 7 Conclusion

7.1. Principal findings

The study investigated, firstly, the viability of a risk parity asset allocation approach on the JSE and compared this to a benchmark of a 60/40 equity and bonds portfolio. Secondly, various methods of applying leverage were explored to understand their effect on cumulative returns and to investigate the theoretical underpinnings of a volatility-timing strategy. The aim was to test a new asset allocation technique on the JSE and develop an investible solution that would maximise investor utility.

Risk parity referred to an asset allocation strategy that aimed to match the risk contributions of each asset class that was included in the portfolio. This was presented as a superior method of achieving diversification, one that would capture market inefficiencies present in pricing low-risk assets available to investors who could take on leverage. The un-levered risk parity portfolio underperformed the 60/40 benchmark in terms of cumulative returns but did so while experiencing lower volatility. The risk parity portfolio appeared less prone to market crashes, outperforming the benchmark during these periods (Asness et al., 2012). Ultimately, un-levered risk parity's risk adjusted return was equal to that of the 60/40 portfolio confirming the international results achieved by Chaves et al. (2011) but in contradiction to those achieved by Asness et al. (2012).

Volatility timing referred to a market timing strategy that aimed to exploit the weak relationship between short-term volatility and short-term return. This was presented as a strategy to achieve a superior mean-variance outcome when applied to an underlying investment style (Moreira & Muir, 2017). The volatility-timing strategy was found not to improve the mean-variance outcome for a risk-parity portfolio on the JSE, in fact, this strategy performed marginally worse than all others tested. While the volatility timing produced the greatest periods of relative gain, it was not immune to market shocks that ultimately erased any prior outperformance.

Academically, this study was one of the first to investigate risk parity as an asset allocation technique on the JSE. It was also the first to apply a volatility-timing strategy to the leverage required by the risk parity strategy. The results for risk parity showed no premium on low-risk assets and no leverage aversion present on the JSE in contradiction to the results found by Asness et al. (2012) in international markets.

The results for volatility-timing also show no mean-variance improvements when applied to risk parity on the JSE. These results show that risk parity and volatility-timing react differently on the JSE than they do in international markets. This may highlight differences in the JSE structure, size and liquidity.

7.2. Implications for management

Practically, this study shows that an investor seeking to outperform a benchmark of a 60/40 portfolio should not consider risk parity as a viable alternative. The risk parity portfolio would require leverage to compete with the 60/40 portfolio on a total return basis which introduces risks not present in the 60/40 portfolio and not represented in the standard mean-variance framework. Significant outperformance would be necessary to compensate for these un-accounted for risks, outperformance that was not evident during the investment window.

This study also highlighted the relative insensitivity of the risk parity portfolio to the timing of leverage. Although different methods of applying leverage resulted in each portfolio taking different path over time, they all converged to a similar result. While each strategy may perform better during specific market conditions, these conditions change over time and would be difficult to identify ex-ante. No economic value was found to timing volatility in a risk parity context. This highlights the value of the Sharpe ratio as a risk-adjusted performance measure which predicted that the un-levered risk parity portfolio would not outperform the 60/40 portfolio once leverage is applied (Sharpe, 1994), regardless of the timing of the leverage.

The Sharpe ratio, and by implication, any portfolio that requires leverage will be very sensitive to the absolute level of the risk-free rate. Holding all else constant, a reduction in the risk-free rate will improve the risk-adjusted returns of portfolios that will require leverage (Sharpe, 1994). This has implications for any investment style that requires leverage and would be a key indicator to the likely success of such a portfolio.

The practical benefits to the investor of diversifying by risk, and adding leverage, have no economic value, providing no greater risk-adjusted returns regardless of how intuitive the investment strategy may be (Thiagarajan & Schachter, 2011).

7.3. Limitations and Recommendations for future research

The study set out to examine the real-world implications of implementing a risk parity strategy on the JSE, comparing the results to a benchmark 60/40 portfolio. The study was subject to various limitations, which together with the disappointing results obtained, served to weaken the case for further research into risk parity as an investment style on the JSE. This study was completed using daily data and rebalancing daily resulting in large shifts in portfolio exposure attempting to capture maximum value. This frequent rebalancing would have a negative effect on the transaction costs involves in such a strategy. These costs would only serve to weaken the attractiveness of risk parity as an investible solution.

Risk parity had shown positive results in more developed markets, suggesting that there was a level of market inefficiency present. Further research into the structural differences in markets and their effect on the viability of risk parity as an asset allocation strategy could provide valuable insight into the conditions that are necessary for risk-parity to outperform. This understanding could not only provide insight into which markets should employ risk parity but also into the conditions that would need to be present on the JSE to dynamically engage and disengage a risk parity strategy with ex-ante information.

The application of a volatility-timing strategy has not been performed on the JSE utilising asset allocation techniques other than risk parity. This timing technique may prove to improve the mean-variance outcome of other techniques such as momentum, value and betting against beta (Frazzini & Pedersen, 2014). Further research into the theoretical implications of applying this strategy to risk parity may provide additional value in markets where risk parity has been shown to be a viable investment alternative.

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Appendix 1 – Ethical clearance

Gordon Institute of Business Science
University of Pretoria

15 August 2018

Gray Peter

Dear Peter

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

You are therefore allowed to continue collecting your data.

Please note that approval is granted based on the methodology and research instruments provided in the application. If there is any deviation change or addition to the research method or tools, a supplementary application for approval must be obtained

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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