AN OVERVIEW OF ASSET ALLOCATION PROCESSES AND THEIR IMPORTANCE IN PORTFOLIO MANAGEMENT

BY

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DECLARATION

I, the undersigned, hereby declare that the work contained in this assignment is my own original work and has not previously in its entirety or in part been submitted at any university for a degree.

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ABSTRACT

Rapid development of asset pricing models, asset return prediction models, information technologies, and the integration and globalisation of world economic markets, require the investor to have a fundamental understanding of the role of asset allocation (diversification) and the various strategies available in achieving investor's risk and return objectives.

Assets are allocated across different asset classes in an attempt to optimise the combination of investment returns and investment risk. In this way your investment will not be subject to the volatility of any one asset class alone. It is important to note that the movements of one class of assets (stocks, bonds or cash) may be somewhat offset by the non-correlated movement of a different class of assets. The intent of asset allocation is not necessarily to increase return as much as it is to find the accepted rate of return, while simultaneously reducing risk or maintaining it at a predefined level.

This study explores the underlying theories concerning the relative importance of asset allocation in determining portfolio performance, and the three primary asset allocation strategies available. It also discusses relevant theory of how the predictability of asset returns and the investment horizon of a portfolio can have an impact on which asset allocation strategy to utilize in achieving the necessary risk and return objectives of the investor.

OPSOMMING

Die toenemende ontwikkeling van bate prys modelle, modelle wat die opbrengs van bates vooruitskat, informasie tegnologie, asook die integrasie en globalisering van internasionale ekonomiese markte, vereis dat die investeerder 'n omvangryke kennis moet beskik oor die rol van bate allokasie (diversifisering) en die verskillende strategië beskikbaar tot die bereiking van investeerder risiko en opbrengs doelwitte.

Bates word geallokeer tussen verskillende bate kategorieë (aandele, effekte of kontant) in die poging om die kombinasie tussen belegging opbrengste en belegging risiko te optimaliseer. Sodoende word die belegging nie blootgestel aan die onbestendigheid van slegs een bate kategorie nie. Daar moet gelet word dat die beweging van een kategorie van bates (aandele, effekte of kontant) teengewerk kan word deur die nie-korrelerende beweging van 'n ander kategorie van bates. Die voorneming van bate allokasie is nie noodwendig die toename van opbrengste nie. Daar word gestreef na die bereiking van 'n aanvaarbare opbrengskoers, terwyl risiko verminder word of volhou word op 'n voorafbepaalde vlak.

Hierdie studie ondersoek die onderliggende teorieë rakende die relatiewe belangrikheid van bate allokasie om portefuelje opbrengste te kan bepaal, asook die drie primêre bate allokasie strategieë beskikbaar. Relevante teorie word bespreek, betreffende die vooruitskatting van bate opbrengste en die horison van 'n portefuelje, asook die impak wat beide het op die keuse van 'n geskikte bate allokasie strategie, om sodoende aan die nodige risiko en opbrengs doelwitte van die investeerder te kan voldoen.

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Introduction

1.1 Background to the Study

> *"Tis the part of a wise man to keep himself today for tomorrow, and not venture all his eggs in one basket"* – Miguel de Cervantes, Don Quixote de la Mancha, 1605.

> *"Behold, the fool saith, 'Put not all thine eggs in the one basket' – which is but a manner of saying, 'Scatter your money and attention'; but the wise man saith, 'Put all your eggs in the one basket and WATCH that basket"* – Mark Twain, Pudd'nhead Wilson, 1894.

Cervantes and Twain were both great writers, but Cervantes would have been the better investor (Lummer & Riepe, 1994: 1). Asset allocation is a form of diversification, in that you do not invest all your assets (eggs) in one asset class (basket). Assets are allocated across different asset classes in an attempt to optimise the combination of investment returns and investment risk. In this way your investment will not be subject to the volatility of any one asset class alone.

What is an asset class? According to Greer (1997: 86), an asset class is a set of assets that bear some fundamental economic similarities to each other and have characteristics that make them distinct from other assets that are not part of that asset class. They are not simply defined by their historical statistical correlation with each other. The movements of one class of assets (stocks, bonds or cash) may be somewhat offset by the non-correlated movement of a different class of assets. The intent is not necessarily to increase return as much as it is to find the accepted rate of return while simultaneously reducing risk or maintaining it at a predefined level.

This study explores the importance of asset allocation for investors, including the primary asset allocation strategies available for investors to achieve their risk and return objectives. This study will discuss the three primary asset allocation strategies:

1. Strategic asset allocation
2. Dynamic asset allocation
3. Tactical asset allocation

Strategic asset allocation is a fixed weight asset allocation strategy, or a set of asset class (stocks, bonds and cash) weights that can be used as a long-term guide for investing. Strategic asset allocation focuses on long-range policy decisions to determine the appropriate asset mix (Droms, 1994: 26). The fixed weight allocation does not mean that you do not rebalance each year, but the weights should be updated occasionally to reflect changes in estimates of the long-term parameters or different needs of the portfolio, according to the inherent risk and return characteristics of each asset class (Lummer & Riepe, 1994: 2). The power of strategic asset allocation lies in its capacity to be tailored to the specific needs of the investor.

Dynamic asset allocation refers to the allocation strategy that continually adjusts a portfolio's allocation in response to changing market conditions. It shifts the content of portfolios between two or more assets or asset classes in response to changes in the portfolio and/or external economic states, on a more-or-less continuous basis (Trippi & Harrif, 1991: 19).

Tactical asset allocation involves a periodic revision of the asset mix in order to improve returns, adjust for risk, or both. Tactical asset allocation is devised to reap the most benefits from shifting market conditions. This strategy principally attempts to overweight or underweight different asset classes at certain times to improve returns.

1.2 Objectives of the Study

Rapid development of asset pricing models, asset return prediction models, information technologies, and the integration and globalisation of world economic markets, require the investor to have a fundamental understanding of the role of asset allocation (diversification) and the various strategies available in achieving investor's risk and return objectives.

This literature study explores the underlying theories concerning the relative importance of asset allocation in determining portfolio performance, and the three primary asset allocation strategies available. It also discusses relevant theory of how the predictability of asset returns and the investment horizon of a portfolio can have an impact on which asset allocation strategy to utilize in achieving the necessary risk and return objectives of the investor.

1.3 Methodology

This study made use of secondary sources of information. A comprehensive literature study of South African and international literature, both published and unpublished, on all the possible aspects pertaining to asset allocation and the objective of this study were undertaken. This was done by means of an examination of books, articles, research works, publications and other relevant literature.

Most of the material that was used for the literature study was of international origin. The literature study was done to obtain insight concerning the present stage of research and application, both nationally and internationally, of the subject of the study.

1.4 Structure of the Study

The study is presented as follows:

<u>Chapter 1</u>: Introduction

This chapter serves as the introductory chapter and provides the background of the study, the main objectives of the study, the methodology and structure of the presentation.

<u>Chapter 2</u>: The Importance of Asset Allocation

This chapter is concerned with the relative importance of asset allocation in the investment decision process. The history and background of asset allocation and its importance in determining portfolio performance is elaborated on. The seminal work of Brinson, Hood, and Beebower (1986), significant to the importance of asset allocation, is discussed in detail. A discussion of the important criticism made against the importance of asset allocation in determining portfolio performance is also presented.

<u>Chapter 3</u>: Factors Influencing Asset Allocation

The predictability of asset returns and the relevance and impact of investment horizon in the asset allocation process are investigated in this chapter, by means of investigating past empirical research. The conventional academic wisdom concerning these two asset allocation issues is questioned and important empirical evidence is presented.

Chapter 4: Strategic Asset Allocation

This chapter sets out to define the concept and relative importance of strategic asset allocation as one of the most important asset allocation strategies. The emphasis of this chapter concerns the mean-variance optimisation methodology commonly used in the investment process. This chapter also presents the scenario-based approach to asset allocation.

Chapter 5: Dynamic Asset Allocation

This chapter discusses the background of dynamic asset allocation, which is followed by the definition encompassing dynamic asset allocation. The characteristics of dynamic asset allocation strategies are presented, as well as the issue concerning concave versus convex strategies, and its relative importance. Three popular dynamic asset allocation strategies are discussed under various scenarios (i.e., bull, bear, and flat markets).

Chapter 6: Tactical Asset Allocation

This chapter sets out to define tactical asset allocation. The history and rationale of tactical asset allocation is followed by discussing two tactical asset allocation methods. The background and effectiveness of market timing and quantitatively derived tactical asset allocation models are presented. The necessary market conditions essential for market timing to add value to a portfolio and the major benefits (adding value) from quantitatively derived tactical asset allocation models are also presented.

Chapter 7: The Future of Asset Allocation

The aim of this chapter is to reflect on the past, present, and future role of asset allocation. Will asset allocation in the nearby future mirror the recent past?

Chapter 2

The Importance of Asset Allocation

2.1 Introduction

Assets are allocated across different asset classes in an attempt to optimise the combination of investment returns and investment risk. Instead of putting all of your eggs in one basket or investing all of your money in one asset class (cash, bonds or stocks), you should diversify across asset classes. In this way your investment will not be subject to the volatility of any one asset class alone.

Different types of investments perform differently under various financial scenarios. Added to that, changes in the financial environment will not have the same impact on all asset classes. Since no one can consistently predict how any type of investment will perform, a diversified portfolio will reduce the impact of underperformance from any one market.

2.2 Background

Arguments on both sides of the fence continue over the importance of asset allocation. Ever since the seminal work of Brinson, Hood, and Beebower (1986), the importance of asset allocation in determining portfolio performance became more scrutinised.

Although not accepted by everyone, the 1986 study of Brinson, Hood, and Beebower and the importance of asset allocation quickly became the topic of debate throughout the financial industry. This study indicates that the asset allocation decision, not the selection of specific stocks or market timing, determines most of the portfolio's variance of returns over time. The growing debate of the relative importance of asset allocation policy in determining portfolio returns spurred many authors to construct their theories and beliefs of whether the asset allocation policy is indeed the main contributing factor to portfolio returns or not.

This chapter first discusses the Brinson, Hood, and Beebower (1986) study in detail. It then presents the main criticism of William Jahnke, who initiated the debate concerning the relative importance of asset allocation in determining portfolio performance, and the importance of the Brinson, Hood, and Beebower study.

2.2.1 The Brinson, Hood, and Beebower Study

2.2.1.1 Introduction

As mentioned above, the origin of the belief in the value of asset allocation is a 1986 study by Brinson, Hood, and Beebower. This pioneering study was followed by an updated study done in 1991 by Brinson, Singer, and Beebower, which confirms the original conclusions.

Brinson, Hood, and Beebower (1986: 39) state that in order to delineate responsibility and measure contribution to performance, investment managers need a clear and relevant method of attributing returns to those activities that compose the investment management process – asset allocation (investment policy), market timing and security selection (investment strategy). The primary goal of this study was to determine, using historical investment data, which investment decisions had the most impact on the extent of total return and on the variability of that return.

According to Brinson, Hood, and Beebower (1986: 40) and Brinson, Singer, and Beebower (1991), the investment policy identifies the long-term asset allocation plan (including asset classes and normal weights) selected to control the overall risk and meet fund objectives. Thus, the policy identifies the entire plan's normal portfolio and it is a specification of the investor's objectives, constraints and requirements, including identification of the normal asset allocation mix.

Active asset allocation, in contrast to investment policy, is seen as the process of managing asset class weights relative to the normal weights over time. The distinction is material to understanding the importance of asset allocation (investment policy) relative to active management (market timing and security selection). Whether active asset allocation involves anticipating price moves (market timing) or reacting to market disequilibria (fundamental analysis), it results in the under or over-weighting of asset classes relative to the normal weights identified by investment policy. The aim is to enhance the return and/or reduce the risk of the portfolio relative to its policy benchmark (Brinson, Singer, & Beebower, 1991: 40).

2.2.1.2 Framework for Analysis

In order to delineate responsibility and measure contribution to performance, Brinson, Hood, and Beebower (1986) developed a framework that can be used to decompose total portfolio returns. Table 2.1 illustrates the framework used to analyse the portfolio returns.

- Quadrant I represents the return from asset allocation, or investment policy return. Here the fund's benchmark return for the period would be placed, as determined by its long-term asset allocation policy. The fund's benchmark return is a consequence of the asset allocation policy adopted by the investor. To calculate the asset allocation policy benchmark return, the following is needed: (1) the weights of all asset classes, specified in advance, and (2) the benchmark return assigned to each asset class.

- Quadrant II represents the return effects of asset allocation and market timing.
- Quadrant III represents returns due to asset allocation and security selection.
- Quadrant IV represents the actual return to the total fund for the period. This is the result of the actual portfolio segment weights and actual segment returns.

Table 2.1: A Simplified Framework for Return Accountability

		Security Selection: Actual	Security Selection: Passive
Market Timing	Actual	(IV) Actual Portfolio Return	(II) Asset Allocation and Timing Return
Market Timing	Passive	(III) Asset Allocation and Security Selection Return	(I) Asset Allocation Return

Active Returns due to:

Market Timing	II – I	
Security Selection	III – I	
Other	IV – III – II + I	
Total		IV – I

Source: Brinson, G., Hood, L. R., & Beebower, G. L. (1986). Determinants of portfolio performance. Financial Analyst Journal. 42(4), 40.

Table 2.2 presents the methods for calculating the values for these quadrants. Table 2.3 gives the computational method for determining the active returns (those due to market timing and/or security selection). Their framework clearly differentiates between the effects of asset allocation (investment policy) and investment strategy (market timing and security selection), and the contribution of the various strategies to total portfolio return.

Table 2.2: Computational Requirements for Return Accountability

		Security Selection: Actual	Security Selection: Passive
Market Timing	Actual	(IV) $\Sigma_i(Wai \cdot Rai)$	(II) $\Sigma_i(Wai \cdot Rpi)$
	Passive	(III) $\Sigma_i(Wpi \cdot Rai)$	(I) $\Sigma_i(Wpi \cdot Rpi)$

Wpi = asset allocation (passive) weight for asset class i

Wai = actual weight for asset class i

Rpi = asset allocation (passive) return for asset class i

Rai = actual return for asset class i

Source: Brinson, G., Hood, L. R., & Beebower, G. L. (1986). Determinants of portfolio performance. Financial Analyst Journal. 42(4), 40.

Table 2.3: Calculation of Active Contributions to Total Performance

Return Due To	Calculated By	Expected Value
Market Timing	$\Sigma_i(Wai \cdot Rpi) - \Sigma_i(Wpi \cdot Rpi)$ (Quadrant II – Quadrant I)	>0
Security Selection	$\Sigma_i(Wpi \cdot Rai) - \Sigma_i(Wpi \cdot Rpi)$ (Quadrant III – Quadrant I)	>0
Other	$\Sigma[(Wai - Wpi) (Rai \cdot Rpi)]$ [Quadrant VI – (Quadrant II + Quadrant III + Quadrant I)]	N/A
Total	$\Sigma[(Wai \cdot Rai) - (Wpi \cdot Rpi)]$ (Quadrant VI – Quadrant I)	>0

Source: Brinson, G., Hood, L. R., & Beebower, G. L. (1986). Determinants of portfolio performance. Financial Analyst Journal. 42(4), 41.

2.2.1.3 Results

Quarterly data from 91 large U.S. pension plans were examined over the 1974 – 1983 period. Table 2.4 summarises the data collected from each plan. Normal weights for each asset class for each plan were not available. Brinson, Hood, and Beebower assumed that the 10-year mean average holding of each asset class would be sufficient to approximate the appropriate normal holding.

Table 2.4: Summary of Holdings of 91 Large Pension Plans, 1974 – 1983

All Holdings	**Average**	**Minimum**	**Maximum**	**Standard Deviation**	**Asset Allocation Benchmark**
Common Stock	57.6%	32.3%	86.5%	10.9%	S&P 500 Total Return Index (S&P 500)
Bonds	21.4	0.0	43.0	9.0	Shearson Lehman Government/Corporate Bond Index
Cash Equivalents	12.4	1.8	33.1	5.0	30-Day Treasury Bills
Other[1]	8.6	0.0	53.5	8.3	None
	100%				
Stocks, Bonds and Cash Only					
Common Stock	63.0%	37.9%	89.3%	10.6%	
Bonds	23.4	0.0	51.3	9.4	
Cash Equivalents	13.6	2.0	35.0	5.2	
	100%				

Source: Brinson, G., Hood, L. R., & Beebower, G. L. (1986). Determinants of portfolio performance. Financial Analyst Journal. 42(4), 41.

Because a complete history of the contents of the "other" component is not available for many plans, Brinson, Hood, and Beebower elected to exclude this segment from most of the analysis. They instead calculated a common stock/bonds/cash equivalent sub-portfolio for use in all quadrants except the total fund actual return, where they used the actual return as reported (including "other"). They constructed the sub-portfolio by eliminating the "other"

[1] Including convertible securities, international holdings, real estate, insurance contracts, mortgag-backed bonds, and private placements.

investment weight from each plan in each quarter and calculating new weights and portfolio returns for the components that remained. This had the effect of spreading the "other" weight proportionately across the remaining asset classes. The bottom panel of Table 2.4 gives the weighting information.

To analyse the relative importance of asset allocation versus investment strategy (market timing and security selection), they calculated the total returns for each of the 91 portfolios. Table 2.5 repeats the framework outlined in Table 2.1 and provides a mean of 91 annualised compound total 10-year rates of return for each quadrant.

Table 2.5: Mean Annualised Returns by Activity, 91 Pension Plans, 1974 – 1983.

		Security Selection	
		Actual	Passive
Market Timing	Actual	(IV) 9.01%	(II) 9.44%
	Passive	(III) 9.75%	(I) 10.11%

Active Returns due to:

Market Timing	-0.66%	
Security Selection	-0.36%	
Other	-0.07%	
Total		-1.10%

Source: Brinson, G., Hood, L. R., & Beebower, G. L. (1986). Determinants of portfolio performance. Financial Analyst Journal. 42(4), 40.

The mean average annualised total return over the 10-year period (Quadrant IV) was 9.01%. This is the return to the entire plan portfolio, not just the common stock/bonds/cash equivalents portion of the plan. The average plan lost 66 basis points per year due to market timing and lost another 36 basis points per year from security selection. The mean average total return for the asset allocation plan (investment policy) for the sample was 10.11% (Quadrant I).

Brinson, Hood, and Beebower (1986) analyses the ability of asset allocation to dictate actual portfolio return further. Table 2.6 examines the relative amount of variance contributed by each quadrant to the return of the total portfolio. It thus addresses directly the relative importance of the decisions affecting total portfolio return. The figures represent the average amounts of total portfolio return explained by each of the quadrants. They were calculated by regressing each plan's actual total return (Quadrant IV) against, in turn, its calculated common stocks/bonds/cash equivalents asset allocation return (Quadrant I), asset allocation and market timing return (Quadrant II), and asset allocation and security selection return (Quadrant III). The value in each quadrant thus has 91 regression equations behind it, and the number shown is the average of 91 unadjusted[2] R-squares of the regressions.

Clearly, the total plan performance explains 100% of itself (Quadrant IV). But, the asset allocation return in Quadrant I explained on average 93.6% of the total variation in actual plan return. Returns due to asset allocation and market timing added modestly to the explained variance (95.3%), as did asset allocation and security selection (97.8%).

Table 2.6 clearly show that total return to a portfolio is dominated by asset allocation decisions. The value added by active management (market timing and security selection) is small, though important, relative to asset class returns as a whole, and describe far less of a portfolio's returns than asset allocation.

[2] This means that the R-squared measures are not adjusted for degrees of freedom; thus, the R-squared represents a square of the correlation coefficient, and represents the amount of variance of total return explained in excess of the average.

The relative magnitudes indicate that asset allocation provides the larger portion of return.

Table 2.6: Percentage of Total Return Variation Explained by Investment Activity, Average of 91 Plans, 1973-1985.

		Security Selection: Actual	Security Selection: Passive
Market Timing	Actual	(IV) 100.0%	(II) 95.3%
	Passive	(III) 97.8%	(I) 93.6%

	Variance Explained: Average	Minimum	Maximum	Standard Deviation
Asset Allocation	93.6%	75.5%	98.6%	4.4%
Asset Allocation and Market Timing	95.3%	78.7%	98.7%	2.9%
Asset Allocation and Security Selection	97.8%	80.6%	99.8%	3.1%

Source: Brinson, G., Hood, L. R., & Beebower, G. L. (1986). Determinants of portfolio performance. Financial Analyst Journal. 42(4), 40.

This would imply that it is the allocation of normal asset class weights and the passive asset classes themselves that provide the bulk of return to a portfolio. Thus, asset allocation is an important determinant of portfolio performance.

2.2.1.4 Implications

The implications of this study revolutionized the portfolio management industry. Data from 91 large U.S. pension plans examined over the 1974 – 1983 period indicate that asset allocation (investment policy) dominates other investment strategies (market timing and security selection) in determining portfolio performance. This study further suggests that although market timing and security selection can result in positive returns, these are dwarfed by the return contribution from asset allocation (investment policy).

According to their findings, the authors also designed a framework of how a portfolio could be constructed in at least four steps (Brinson, Hood, & Beebower, 1986: 43):

1. Deciding which asset classes to include and which to exclude from the portfolio;
2. Deciding upon the normal, or long-term weights for each of the asset classes allowed in the portfolio;
3. Strategically altering the investment mix weights away from normal in an attempt to capture excess returns from short-term fluctuations in asset class prices (market timing); and
4. Selecting individual securities within an asset class to achieve superior returns relative to that asset class (security selection).

The first two decisions are part of asset allocation (investment policy); the last two are part of market timing and security selection. As can well be observed, concentration is on the overwhelming impact of asset allocation, however established, and the incremental effect of active management strategies.

2.2.2 Criticism of the Importance of Asset Allocation

It should be noted that criticism made against the importance of asset allocation as a contributing factor to portfolio performance, is not about the benefits of diversifying risk by spreading investments among different asset classes. This is about performance, and the importance of asset allocation in determining it.

Since the pioneering work of Brinson, Hood, and Beebower (1986), most investors and investment advisors have operated with the belief that asset allocation explains more than 90% of portfolio performance. As mentioned earlier, this study is now still at the centre of a debate, a debate initiated by Jahnke (1997) in "The Asset Allocation Hoax".

2.2.2.1 Jahnke's Criticism and Comments

Jahnke (1997) argues that the Brinson, Hood, and Beebower study (1986) used the wrong approach, including mathematical differences and data capturing. He argues that asset allocation actually explains only 14.6% of portfolio performance in the Brinson, Hood, and Beebower study (1986).

Jahnke (1997) notes that the ten-year annual returns of the 91 benchmark portfolios used (see Table 2.7), ranged from 9.47% to 10.57% (a spread of 1.1 percentage points), while the ten-year annual returns of the 91 actual portfolios ranged from 5.85% to 13.4% (a spread of 7.55 percentage points). The expected range of 1.1 percentage points divided by the actual range of 7.55 percentage points equals 14.6%, thus, Jahnke's assertion that asset allocation only explains 14.6% of portfolio performance, as opposed to 93.6% (O'Rielly & Chandler, 2000: 95).

Table 2.7: Annualised 10-Year Returns of 91 Large Pension Plans, 1974 – 1983.

Portfolio Total Returns	Average Return	Minimum Return	Maximum Return	Standard Return
Policy	**10.11%**	**9.47%**	**10.57%**	0.22%
Policy and Timing	9.44%	7.25%	10.34%	0.52%
Policy and Selection	9.75%	7.17%	13.31%	1.33%
Actual Portfolio	**9.01%**	**5.85%**	**13.40%**	1.43%

Source: Brinson, G., Hood, L. R., & Beebower, G. L. (1986). Determinants of portfolio performance. Financial Analyst Journal. 42(4), 40.

Jahnke's (1997) criticism can be shown to be invalid, though, using two examples.

1. Assume there had been a 92nd portfolio included in the Brinson, Hood, and Beebower study with a benchmark return of 4% (thus, the minimum return of an asset allocation portfolio, shown in Table 2.7, changes from 9.47% to 4%). This would increase the spread of the benchmark portfolios used, from 1.1 to 6.57. Given an actual return within the range of returns observed by Brinson, Hood, and Beebower, Jahnke's ratio would lead us to conclude that asset allocation accounted for 87% (6.57/7.55) of the results. This figure would justify Brinson, Hood, and Beebower's study.

2. Jahnke (1997) used the spread between the ranges (minimum and maximum returns) of the 91 benchmark portfolios to prove that asset allocation only explains 14.6% of portfolio performance. If one uses Jahnke's ratio, and calculate the *average* returns of the asset allocation portfolio (10.11%) and the actual portfolio (9.01%), though, the average fraction of actual returns attributable to asset allocation in the study is 112% (10.11/9.01). Clearly, Brinson, Hood, and Beebower (1986) would have quoted this figure, instead of 93.6%, if they believed that Jahnke's ratio was indeed the correct method of calculation of return contribution.

Jahnke (1997) also criticises the fact that the performance data used by Brinson, Hood, and Beebower (1986) were gross of management fees and that their use of quarterly data dampens the impact of compounding slight portfolio return disparities relative to the benchmarks. According to O'Reilly & Chandler (2000: 95), however, their failure to use net return data does not invalidate their conclusions as to the importance of asset allocation.

2.3 Asset Allocation Vindicated?

This chapter presented arguments made in favour of the importance of asset allocation based on the pioneering study by Brinson, Hood, and Beebower (1986), as well as criticism against the importance of asset allocation as a contributing factor of portfolio performance.

Is the Brinson, Hood, and Beebower (1986) statement true or false? That is the question that stimulated the debate regarding the importance and role that asset allocation should play in investment management. Jahnke (1997), as mentioned above, initiated this debate, criticising this outrageous figure of 93.6% as opposed to his estimation of 14.6%. Then again, this chapter have shown that Jahnke's method of calculation can also be used to justify Brinson, Hood, and Beebower's (1986) findings. Thus, Jahnke's (1997) major criticisms and comments, as shown in the section above, does not invalidate Brinson, Hood, and Beebower's conclusions as to the importance of asset allocation as a major contributing factor to portfolio performance. These general observations indicate that asset allocation plays a dominant role in determining the variability of portfolio performance.

No other research, relevant to this debate, other than those either protesting the same charges made by Jahnke or defending the Brinson, Hood, and Beebower study were found. It is recommended that more original research should be conducted regarding this topic, especially a more comprehensive analysis of the Brinson, Hood, and Beebower study.

2.4 Summary

- Assets are allocated across different asset classes in an attempt to optimise the contribution of investment returns and investment risk.

- Different types of investments perform differently under various financial scenarios. Added to that, changes in the financial environment will not have the same impact on all asset classes. A diversified portfolio will reduce this impact of underperformance from any one market.

- Since investors all have their own objectives and tolerances for risk, individual asset allocations, or the way investments are divided among cash, bonds and stocks can be very different.

- Asset allocations' intent is not necessarily to increase return as much as it is to find the accepted rate of return, while simultaneously reducing risk or maintaining it at a predefined level.

- According to Brinson, Hood, and Beebower (1986) and Brinson, Singer, and Beebower (1991), the investment policy identifies the long-term asset allocation plan (included asset classes and normal weights) selected to control the overall risk and meet fund objectives.

- Jahnke (1997) argues that the Brinson, Hood, and Beebower (1986) study used the wrong approach, including mathematical differences and data capturing. Thus, according to Jahnke (1997), asset allocation is not critical in determining portfolio performance.

- Jahnke's criticisms do not invalidate Brinson, Hood, and Beebower's conclusions as to the importance of asset allocation.

- The observations herein indicate that asset allocation plays a dominant role in determining the variability of portfolio performance.

Chapter 3

Factors Influencing Asset Allocation

3.1 Introduction

The asset allocation decision is an important factor in determining portfolio performance and achieving an investor's objectives. Choosing the right mix of assets and the appropriate horizon of the investment are important factors in the asset allocation process. Understanding the behaviour of security returns or having the ability to predict returns in the stock and bond markets would increase the probability of choosing the right mix of assets, and therefore increase the probability of meeting investors' objectives. While the mix of assets an investor chooses affects investment outcome more than other, the chance of meeting investment objectives also depends on the investor deciding on an appropriate investment horizon.

3.2 Return Predictability

The conventional academic wisdom regarding the predictability of asset returns has shifted dramatically over the past decade. While early empirical evidence favoured the random walk hypothesis for asset returns, accumulating empirical evidence now suggests that asset returns are predictable.

Finding cracks in the efficient market hypothesis became a research industry for empirical finance specialists during the 1980s and early 1990s. During the early 1970s, the profession had come to believe that markets reasonably well reflected at least all publicly available information so that it was not possible for investors trading on fundamental information to outperform a buy and hold strategy involving a widely diversified group of securities with equivalent risk (Fluck & Malkiel, 1997: 184).

By the mid-1990s more and more literature had appeared that suggested it was possible to predict returns on the basis of past returns and fundamental ratios such as relative size, dividend yields, price-book ratios, and price-earnings multiples (Fluck & Malkiel, 1997: 184).

3.2.1 Stock Return and Inflation

A puzzle of the 1970s was to explain why monthly stock returns are negatively related to expected inflation and the level of short-term interest rates. Expected inflation, unexpected inflation, and changes in expected inflation are all negatively related to stock returns. Fama and Schwert (1977) found a consistent negative relation between stock returns and both expected inflation and changes in those expectations (Geske & Roll, 1983: 1).

Geske and Roll (1983: 1) give an explanation for this phenomenon. They find that stock returns are negatively related to simultaneous changes in expected inflation because they signal a chain of events, which results in a higher rate of monetary expansion. Shocks in real output, signalled by the stock market, induce changes in tax revenue, in the deficit, in Treasury borrowing and in the Reserve Bank's monetisation of the increased debt. Bond and stock market investors realize this will happen. They adjust prices, and interest rates, accordingly and without delay. Thus, positive (negative) stock returns are likely to be related to negative (positive) changes in the real interest rate. Accordingly, stock returns may be negatively related to changes in the T-Bill rate, a useful proxy for expected inflation.

3.2.2 Dividend Yield

Fama and French (1988) use regressions of returns on dividend yields to track expected returns. They use dividend yields to forecast returns on the value-weighted and equally weighted portfolios of NYSE stocks for horizons from 1 month to 5 years, because dividend yields explains small fractions of monthly and quarterly return variances. This study shows that low dividend yields imply low expected returns.

Keim and Stambaugh (1986: 357) find that several predetermined variables that reflect levels of bond and stock prices appear to predict returns on common stocks of firms of various sizes, long-term bonds of various default risks, and default-free bonds of various maturities. The stock and bond returns are predictable from a common set of stock market and term structure variables that include:

1. The spread between yields on low-grade corporate bonds and one month T-Bills, and
2. Minus the logarithm of the ratio of the real S&P's index to its previous historical average.

Keim and Stambaugh (1986: 359) also find that the variables used in their study predict differences between asset class returns.

Fama and French (1989) argue that any model employing stock market and term structure variables to predict asset class returns must be continually respecified over time. They show that the dividend yield on the NYSE value-weighted portfolio indeed forecasts the return on corporate bonds as well as common stocks. They also suggest a different way to judge the implications of return predictability for market efficiency. They argue that there are systematic patterns in the variation of expected returns through time. They also find that the variation in expected returns tracked by dividend yield and the default spread (the slopes in the regressions of returns on dividend yields or the default spread) increase from high-grade bonds to low-grade bonds, from bonds to stocks, and from large stocks to small stocks. This ordering corresponds to intuition about the risks of the securities. Thus, they find that the variation in expected returns increase as the security's risk increases. Therefore, Fama and French (1989) argue that the variation in expected returns on corporate bonds and common stocks tracked by their individual dividend yield, default spread, and term spread variables is related to business conditions (Fama, 1991: 1610).

3.2.3 Other Financial and Economic Variables

More studies on stock return predictability include Balvers, Cosimano, and McDonald (1990), Breen, Glosten, and Jagannathan (1990), Cochrane (1991), Ferson and Harvey (1993), Glosten, Jagannathan, and Runkle (1993). All of these studies find that publicly available information, such as financial time series data and macroeconomic variables, can predict a significant portion of stock returns. Despite the difficulty in economic interpretation, the conclusion holds across international stock markets as well as over different time horizons (Qi, 1999: 421).

Using a recursive linear regression modelling[3] approach, Pesaran and Timmermann (1995) examined the robustness of the evidence on predictability of U.S. stock returns by simulating the decision process of an investor who, at each point in time, uses only historically available information and a predefined model-selection criterion to select a set of economic factors. The chosen set of variables

[3] Linear regression is by far the most popular model in studies of stock-return prediction using financial and economic variables. It is easy to estimate and interpret, and the statistical properties of its estimators are readily available for statistical inference and hypothesis testing. With relatively low computational cost, it produces reasonably good forecasts across a diverse set of series.

is then used to make one-period-ahead prediction of excess returns, and the resulting recursive forecasts are employed to make investment decisions. They find that the predictive power of various economic factors over stock returns, as opposed to the section above, changes over time and tends to vary with the market volatility (Qi, 1999:425). Consequently, they suggest that the predictive power of the various economic factors over stock returns should be used for short-term market predictions. This would be useful for tactical and/or dynamic asset allocation strategies, utilizing short-term market predictions gainfully.

3.2.4 Alternative Return Prediction Model

Neural networks are a class of generalised non-linear models inspired by studies of the brain and nerve system. The comparative advantage of neural networks over more conventional econometric models, such as linear regression models, is that they can approximate any non-linear (or linear) function to a degree of accuracy with a suitable number of hidden units through the composition of a network of relatively simple functions. The recent development in neural network theory even allows the construction of valid prediction intervals (Qi, 1999: 425).

Neural networks are an ideal choice for flexible non-linear modelling and are gaining attention in the area of stock-return prediction. Given the numerous empirical findings that stock returns are linearly predictable using some financial and economic variables, Qi (1999) researched the usefulness of non-linear models in stock-return prediction using financial and economic variables. Many financial series have recently been found essentially non-linear in nature (Abhyankar, Copeland, and Wong, 1997). These findings provide strong motivation for assessing the predictability of stock returns using non-linear models (Qi, 1999: 420).

Qi (1999: 420), using neural networks, extends the research by Pesaran and Timmerman (1995) in the previous section, by changing the investor's choice set. Instead of being open-minded in selecting economic factors, the investor is liberal in selecting the functional form through which the chosen economic factors predict stock-market returns. The investor is not confined to linear models; one is free to choose from a set of linear and non-linear models.

3.2.5 Return Predictability, Profitability, and Importance for Asset Allocation

The empirical evidence presented, suggest that although asset returns are predictable, the predictive power of the various influencing factors should be used for short-term market predictions, because of high market volatility over longer periods of time. Short-term market predictions could be useful for tactical and dynamic asset allocation strategies in the process of choosing the right mix of assets and achieving the investor's objectives. Predictability does not necessarily imply profitability though. Whether the investor can make profit, how much profit the investor can make, and how much risk the investor has to bear to make so much profit, depend in addition on what trading strategy one uses and the magnitude of transaction costs. Especially when the positions are evaluated monthly based on monthly recursive forecasts, the profits may be eroded by transaction costs. As such, an investment strategy that is based on recursive forecasts (dynamic and tactical asset allocation strategies, as opposed to strategic asset allocation) is likely to incur higher transaction costs and may not be as profitable as the buy-and-hold strategy.

Meeting the investor's objectives, however, also depends on the investor deciding on an appropriate investment horizon, which also influences the recommended asset class proportions that will satisfy the investor's risk and return objectives.

3.3 Investment Horizon

An important practical question that financial theory should address is how the investment horizon affects risk, and therefore the allocation of funds to the various asset classes? Different investment horizons require different asset class proportions that will satisfy the investor's risk and return objectives. Portfolio managers manage risk, and therefore, you would expect that the horizon of your investment would certainly have an effect on your portfolio proportions due to the different asset class risks over time and transaction costs.

3.3.1 Horizon and Risk

"Lengthening the horizon might modify the portfolio risk for investors" (Bierman, 1997:51). This statement will be discussed by considering whether the investment horizon affects the investor's decision to invest in stocks (risky investment).

Thorley (1995) examines the outcomes of two investment options, shown in Table 3.1. One alternative is risk-free, and one is with risk and a higher expected return. The probability of underperformance of the risky investment decreases as the horizon increases. If the horizon is one year, the probability of underperformance of the risky investment is 30.9%, and it is 0.1% for a horizon of forty years.

Given that Thorley uses a 4% risk-free return and a 12% risky expected return, and given a long time horizon, the 800 basis point difference makes itself felt by increasing the likelihood that stocks will be better than the lower yielding risk-free investment as the investment horizon lengthens. Thus, if one measures the riskiness of an investment by the probability of a shortfall compared to a target on termination of the investment, the investment horizon affects the probability.

In stark contrast to the above, Samuelson (1990: 5) concludes that the investment horizon can have no effect on your portfolio proportions. Bodie (1995) also shows that the cost of insuring against a shortfall with an investment in stock increases as the time horizon increases. He states that "if investors act so rationally to maximise the expected utility of consumption over their lifetimes, then an investment's age per se has no predictable effect on the optimal proportion to invest in stocks" (1995: 20).

Table 3.1: Risk-Free versus Risky Options under Various Investment Horizons: Initial Investment of R1000.

		Risky Value (R)			Underperformance	
Horizon (years)	Risk-Free Value (R)	Mean	10 Percentile	90 Percentile	Probability (%)	Risky Mean (R)
1	1.041	1.142	918	1.384	30.9	942
5	1.221	1.943	1.152	2.882	13.2	1.032
10	1.492	3.773	1.736	6.350	5.7	1.222
20	2.226	14.239	4.406	27.578	1.3	1.776
40	4.953	202.755	33.220	444.451	0.1	3.875

Source: Thorley, S. R. (1995). The time diversification controversy. Financial Analyst Journal. 51(3), 69.

Bodie (1995) computes the cost of the put options necessary to insure a minimum return. He finds that the total cost of insurance increases, the longer the horizon.

Bierman (1997: 51) find that Bodie's approach require further consideration, because:

1. The average of total increases per year and the marginal costs of the insurance decrease as the time horizon increase; and
2. The arbitrage model used in Bodie's research uses the variance of the future stock price, but not the expected return, while the expected return on stocks is very important to the investor making the allocation decision according to Bierman (1997).

Bierman (1997: 52), arguing that lengthening the investment horizon might modify the portfolio risk for investors, considers whether the investment horizon affects the investor's decision to invest in stocks. He defines risk for a period to be the expected value when the investment earns less than the risk-free rate for a given investment. Bierman explains that investment horizon affects risk with the following three examples.

Example 1: Assume the risk-free rate is 5%, and that a R1 million investment in stock will earn 12% with 0.8 probability or 2% with 0.2 probability. The relevant outcomes are shown in Exhibit 3.1.

The expected loss for this one period, if the bad event (0.2 probability of a loss) occurs, is R6 000. If there are subsequent periods with identical investments, the expected loss will increase. With no change in the outcomes or probabilities, the cumulative risk, as defined above, will increase by R6 000 for each period we add to the horizon. This is consistent with the positions of Samuelson and Bodie. The cost of insurance against loss increases as the number of periods increases. Bierman (1997: 52) asserts that this example that leads to a conclusion of more risk with a lengthening of the horizon consider only the outcomes that the investment earns less than the target amount, and thus generates a loss with a given probability. He argues that one should consider an interpretation of risk that includes the good outcomes as well as the bad outcomes. He illustrates this argument by comparing lengthening the horizon of common stock to a gamble in Example 2 and Example 3.

Exhibit 3.1: Possible Outcomes

Probability	Conditional Outcome	Conditional Gain or Loss Compared to 0.05	Expectation of Gain or Loss
0.8	R120 000	R70 000	R56 000 Gain
0.2	R20 000	(R30 000)	(R6 000) Loss

Source: Bierman, H. (1997). Portfolio allocation and the investment horizon. Journal of Portfolio Management. 23(4), 52.

Example 2: Imagine you bet R100 000, and you obtain R200 000 with 0.52 probability or zero with 0.48 probability. The expected value of the payoff is shown in Exhibit 3.2.

The expected value is positive (+ R4000), but there is a 0.48 probability of losing R100 000. Because of risk aversion, most investors will reject this opportunity to invest in this gamble, despite the fact that it is a fair gamble with a R4000 expected value. The 0.48 probability of a R100 000 loss is too large a probability and too large a loss to accept the investment, given your utility function (Bierman, 1997: 53).

Exhibit 3.2: Possible Outcomes of Gamble – R100 000

Expected Outcomes Without Outlay		Expected Outcomes With R100 000 Outlay	
R200 000 x 0.52 =	R104 000	R100 000 x 0.52 =	R52 000
0 x 0.48 =	R 0	(R100 000) x 0.48 =	(R48 000)
Expected Value	R104 000	Expected Value	R4 000

Source: Bierman, H. (1997). Portfolio allocation and the investment horizon. Journal of Portfolio Management. 23(4), 52.

Example 3: Assume a gamble costing R10 000 that will pay R20 000 with 0.52 probability or zero with 0.48 probability. But now assume the investor plays this gamble ten times. The probability of losing ten times in a row or losing R100 000 in total is now only 0.0006 [$(0.48)^{10} = 0.0006$].

Decreasing the probabilities of the extreme negative outcomes is attractive. Given the fact that this is a fair gamble, multiple trails enhance the desirability of this Example 3 compared to Example 2, despite the fact that the expected value of the ten trails is again R104 000 gross and R4000 net (Bierman, 1997: 53).

Exhibit 3.3: Possible Outcomes of Gamble – R10 000

Expected Outcomes Without Outlay		Expected Outcomes With R10 000 Outlay	
R20 000 x 0.52 =	R10 400	R10 000 x 0.52 =	R5 200
0 x 0.48 =	0	(R10 000) x 0.48 =	(R4 800)
Expected Value	R10 400	Expected Value	R400

Source: Bierman, H. (1997). Portfolio allocation and the investment horizon. Journal of Portfolio Management. 23(4), 52.

Each additional trail increases the expected value of the gambling sequence and decreases the probability of the extreme outcomes. Lengthening the time horizon for common stock investment is analogous to increasing the number of the illustrated gamble. Increasing the number of time periods gives the fair nature of the gamble an opportunity to outweigh the loss outcomes (Bierman, 1997: 53).

Bierman (1997: 53) finds that as long as:

1. The expected return significantly favours common stock;
2. The probability of a good return for each year is significantly higher than the probability of a loss; and
3. The returns of each year have a correlation that is closer to zero than to one; the horizon will affect the risk, where risk is defined as the probability of a loss.

Thus, Bierman (1997: 54) uses expectations and utility functions of investors, and finds that increasing the investment horizon gives the fair nature of the gamble (stocks) an opportunity to outweigh the loss outcomes, assuming their utility functions use as an input the probability of stocks earning more than the risk-free rate over the relevant time period. Consequently, the risk of holding equities over long periods of time will be lower than the risk associated with holding them for just one year or very short periods.

3.3.2 Time Diversification

Bierman (1997), in the section above, finds that lengthening the time horizon for common stock investment is analogous to increasing the number of a gamble. Increasing the number of time periods gives the fair nature of the gamble (stocks) an opportunity to outweigh the loss outcomes. Most practitioners take as a given that the longer the investor holds risky assets, such as stocks, the more the investor will benefit from what is often called time diversification. For example, investors with a very long time horizon are advised to allocate more funds to equity investments than should older savers whose retirement is imminent (Thorley, 1995: 68).

The popular logic that supports time diversification is simple. If stock market returns are independent from one year to the next, then good years in the market will offset the bad years, and the risk of holding equities over long periods of time will be lower than the risk associated with holding them for just one year (Thorley, 1995: 69).

An analogy is made to the more common principle of diversification across risky assets. The principle states that if individual asset returns are not perfectly correlated, then a portfolio of assets will have less risk than the individual assets alone. Because successive returns on a single asset are uncorrelated over time, it would seem to follow that the risk of owning a single stock is lower if it is held for many years, instead of just one (Thorley, 1995: 69).

According to Thorley (1995: 68), practitioner-oriented research assumes the validity of time diversification and concerns itself with measuring its economic significance. Research of a more academic nature, however, has repeatedly rejected the notion of time diversification. This rejection is based on economic models of risk aversion that suggest that an investor who is not willing to commit funds to the stock market for 1 year would likewise not be willing to commit funds to the market for 20 years.

But, Thorley (1995: 73) finds that these arguments are a misapplication of the positive economic paradigm. He states that critics of time diversification have inappropriately applied models of investor preference that are adequate for short horizons to the question of asset allocation over very long horizons. In this context, the distinction between positive (descriptive) and normative (prescriptive) economic theory is important. It is important to note that most economic models are positive in nature. They attempt to describe, as simple as possible, how rational economic agents in the real world make choices and then to predict the consequences of those choices. The normative application of these models to arguments about what agents should do is seldom the intent of the theory.

3.3.3 Transaction Costs

Gunthorpe and Levy (1994: 53) reveal that investors with different holding periods will have different optimal portfolio compositions. The differences primarily reflect differences in investor's transaction costs. Large investors (e.g., institutional investors) face relatively low transaction costs, so they can plan to revise their portfolios frequently (e.g., monthly or weekly). Small investors, by contrast, face relatively high transaction costs, which prohibits them from planning short investment horizons.

Gunthorpe and Levy (1994) assume that investors use mean-variance analysis to make their portfolio decisions and demonstrate that changes in investment horizon can affect both portfolio beta and portfolio composition. They believe that if returns are dependent and nonstationary over time, the assumed holding period will affect portfolio composition. In their research, they assumed that returns are independent and stationary over time, and that lead them to believe that the assumed holding period will not affect portfolio composition. However, contrary to the assumption made, they demonstrate that mean-variance portfolio composition is a function of the assumed holding period. They find that variance and beta change in a very complex manner in response to changes in the number of period n. This means that portfolio composition will change with the assumed holding period.

3.3.4 Asset Allocation Strategies and Investment Horizon

A study by Brennan, Schwartz and Lagnado (1997) confirms the important role that investment horizon plays in the asset allocation process. They find that the investor's time horizon has a significant effect on the composition of the optimal portfolio. They consider stocks, bonds and cash, and their optimal proportions over various investment horizons. The optimal portfolio proportions of an investor with a long horizon (strategic asset allocation) are compared with those of an investor with a short horizon such as typically assumed by tactical asset allocation models. They are found to be significantly different.

The time variation is assumed to be driven by three state variables; the short-term interest rate; the rate on long-term bonds; and the dividend yield on a stock portfolio. The three state variables are all assumed to follow a joint Markov process. The process is estimated from empirical data (January 1972 to January 1992) and the investor's optimal control problem is solved numerically for the resulting parameter values.

The portfolio proportions are calculated for three distinct strategies. First, under the assumption that the horizon is a constant 20 years (strategic asset allocation) – the 20-year strategy. Secondly, under the assumption that the horizon is always 1 month – the one-month strategy. This strategy is intended to represent the myopic strategy that underlies tactical asset allocation. Finally, under the assumption that the horizon is 1 January 1992 – the 1992 strategy. Under this strategy the horizon used to calculate the portfolio proportions in any given month is the number of months remaining to January 1992 (Brennan, Schwartz & Lagnado, 1997: 1393).

Brennan, Schwartz, and Lagnado found that the cash proportions under all three strategies varied between zero and 90%, and is highly volatile. The tactical asset allocation strategy displays a higher cash position than the constant 20-year strategic asset allocation strategy. The reason for this is that cash is assumed to be risk-less over a one-month horizon. It is not assumed to be risk-less for a 20-year horizon because of the uncertainty surrounding the reinvestment rate. The 1992 strategy cash proportion starts out the same as the 20-year strategy and converges to that of the one-month strategy (Brennan, Schwartz & Lagnado, 1997: 1394). This is because the 1992 strategy changes from a 20-year (strategic asset allocation) strategy to ultimately a one-month (tactical asset allocation) strategy.

The stock proportions for all three strategies ranged between zero and 100% and are also highly volatile. They find that the 20-year strategy always invest more in stock than the one-month strategy. The reason for this is that stocks are less risky for those with a long horizon, as suggested by Bierman (1997) and Thorley (1995). As before, the 1992 strategy is intermediate between these two (Brennan, Schwartz & Lagnado, 1997: 1395).

Their results indicate that an investor with a long horizon, following a strategic asset allocation strategy, typically places a larger fraction of the portfolio in both stocks and bonds than does a myopic investor, following a tactical asset allocation strategy. They find that the reason for this could be the result of mean reversion in both stock and bond returns that make these assets less risky from the viewpoint of a long-term investor. Equivalently, investments in stocks, and more particularly bonds, provide the long-term investor with a hedge against future adverse shifts in the investment opportunity set – by buying long-term bonds, the investor protects himself against declines in future interest rates (Brennan, Schwartz & Lagnado, 1997: 1377).

3.4 Summary

- Choosing the right mix of assets and the appropriate horizon of the investment are important factors in the asset allocation process.

- Understanding the behaviour of security returns or having the ability to predict returns in the stock and bond markets would increase the probability of choosing the right mix of assets, and therefore increase the probability of meeting investors' objectives.

- The conventional academic wisdom regarding the predictability of asset returns has shifted dramatically over the past decade. While early empirical evidence favoured the random walk hypothesis for asset returns, accumulating empirical evidence now suggests that asset returns are predictable.

- The predictive power of the various economic factors over stock returns should be used for short-term market predictions. This would be useful for tactical and/or dynamic asset allocation strategies, utilizing short-term market predictions gainfully.

- Predictability does not necessarily imply profitability. Whether the investor can make profit, how much profit the investor can make, and how much risk the investor has to bear to make so much profit, depend in addition on what trading strategy one uses and the magnitude of transaction costs.

- Meeting the investor's objectives depends on the investor deciding on an appropriate investment horizon, which also influences the recommended asset class proportions that will satisfy the investor's risk and return objectives.

- Different investment horizons require different asset class proportions that will satisfy the investor's risk and return objectives.

- Lengthening the horizon might modify the portfolio risk for investors. For example, the risk of holding equities over long periods of time will be lower than the risk associated with holding them for just one year or very short periods.

- The investor's time horizon has a significant effect on the composition of the optimal portfolio.

Chapter 4

Strategic Asset Allocation

4.1 Introduction

Strategic asset allocation is a fixed weight asset allocation strategy, or a set of asset class (stocks, bonds and cash) weights that can be used as a long-term guide for investing. Strategic asset allocation focuses on long-range policy decisions to determine the appropriate asset mix (Droms, 1994: 26).

The fixed weight allocation does not mean that you do not rebalance each year, but the weights should be updated occasionally to reflect changes in estimates of the long-term parameters or different needs of the portfolio, according to the inherent risk and return characteristics of each asset class (Lummer & Riepe, 1994).

4.2 Background

Early influential studies by Brinson, Hood, and Beebower (1986) and Brinson, Singer, and Beebower (1991) imply that the asset allocation decision is the key determinant of portfolio returns. These studies also conclude that individual security selection is of limited importance. For this reason, asset allocation decisions represent the key challenge for investment managers (Lamm & McFall, 2000: 27).

The strategic asset allocation approach is based on three intuitively appealing and generally accepted assumptions (Droms, 1994: 26):

1. Risk and return go hand-in-hand in the capital markets – the higher the risk, the higher the return and vice versa.
2. The capital markets are reasonably efficient over the long run and future return spreads will be similar to historical spreads – at least in direction.
3. Market timing is not likely to enhance long-term investment results.

The implication of these three assumptions is that any asset allocation model should take a long-term, strategic approach to asset allocation and any resulting portfolio should offer broad diversification among asset classes.

As mentioned, the portfolio is rebalanced periodically, typically on a calendar year basis, in order to maintain the original proportions. No attempt whatsoever is made to predict short-term performance, or to change the asset mix to match current market conditions. It should be stressed that this strategy is geared entirely to the goals and situation of a specific investor. In addition, an asset allocation system must be a function of an investor's return needs, including consideration of income and capital growth, risk tolerance, including risk aversion[4], loss aversion, and liquidity preference.

4.3 Mean-Variance Optimisation

Most portfolio allocation decisions made today rely on Markowitz (1959) mean-variance optimisation or variants of the method. This approach explicitly compels

[4] Risk aversion is the classical hypothesised behaviour of the "rational economic person" faced with making a decision involving risk. The rational economic person is assumed to make investment choices that maximise expected return at any given risk level or, alternatively and equivalently, minimise risk at any given return level (Droms, 1994: 26).

the use of comprehensive risk management because probability is required in portfolio construction (Lamm & McFall, 2000: 27).

Mean-variance optimisation refers to a mathematical process that calculates the security or asset class weights that provide a portfolio with the maximum expected return for a given level of risk; or conversely, the minimum risk for a given expected return (Lummer & Riepe, 1994: 2).

The consequence of mean-variance optimisation is a set of asset class weights that can be used as a long-term guide for investing, which is described as the portfolio's strategic asset allocation plan (Lummer & Riepe, 1994: 2).

4.3.1 Background

Although mean-variance optimisation is over 40 years old, its use as an applied portfolio management tool has only recently become extensive. Its origins are well known and it has been the most popular quantitative methodology for asset allocation and portfolio diversification (Koskosidis & Duarte, 1997: 74).

Mean-variance optimisation models have been widely used with considerable success for asset allocation (Fong & Fabozzi, 1988) and (Zenios, 1993) (cited in Koskosidis & Duarte, 1997: 75). According to Nairne (1994: 52), strategic asset allocation is a reliable tool for optimising a portfolio for two reasons:

1. Over the long run, capital markets are rational. Higher-risk investments must, on average, pay out higher returns. This is known as the equity risk premium. Thus, to increase long-term returns in a portfolio, one simply increases the portion allocated to equities relative to fixed-income securities.

2. An increase in portfolio returns does not have to be accompanied by a commensurate increase in risk if the portfolio is properly diversified. Each asset group performs differently at different stages in the business cycle.

This all boils down to diversification. One can reduce overall volatility by combining different asset groups. The strategically balanced portfolio will provide the expected long-term results, but with considerably less volatility along the way (Nairne, 1994: 52).

4.3.2 Limitations

Mean-variance optimisation models have attracted a fair amount of criticism as portfolio managers have found that these models are difficult to use in practice, and that the portfolios they generate are often unreasonable and counter-intuitive (Best & Grauer, 1991) (cited in Koskosidis & Duarte, 1997: 75).

The traditional mean-variance optimisation technique (along with the semi-variance and the absolute deviation based variants), tend to rely heavily on forecasts of the expected return, the expected volatility, and the expected cross-correlation of the assets under consideration. These forecasts, in turn, are driven by some kind of historical average market behaviour over a period in the past. A drawback is that as world economic conditions and the financial markets change, historical averages might not be representative of current market conditions (Koskosidis & Duarte, 1997: 74). Thus, small deviations could swing the portfolios to extreme solutions.

The problem is compounded by the fact that asset returns, volatility, and correlations are very difficult to estimate accurately. Many users of mean-variance optimisation obtain poor results largely because of these errors (estimation error) in forecasting asset returns or risk (Lamm & McFall, 2000: 28). Although this is inherent in any kind of asset allocation scheme, traditional mean-variance optimisation models tend to be particularly sensitive, since they require a single-point forecast for these variables. The forecasts are typically derived from the average behaviour of the assets during some more or less arbitrarily chosen past period, which might not be representative of the current conditions (Koskosidis & Duarte, 1997: 75).

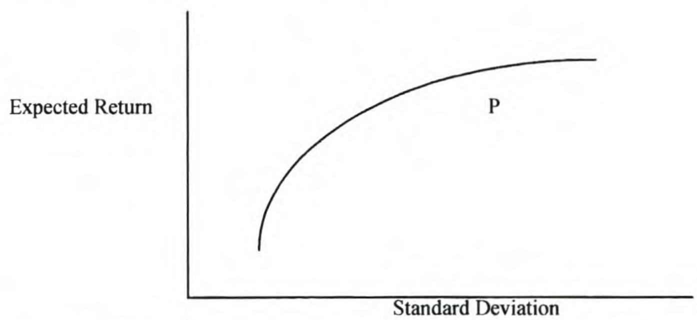
Furthermore, standard optimisation models cannot take into account the varying degrees of confidence of investors in the forecasts, nor can they incorporate investors' uncertainty about some markets. Investors might follow and understand some markets better than others, and might have strong views on some but not on others. Standard optimisation models cannot distinguish between strong and weak views, but treat them all the same (Koskosidis & Duarte, 1997: 75).

4.3.2.1 Example of the Effects of Estimation Error and Unstable Solutions

As mentioned previously, the inputs needed for mean-variance optimisation are expected returns, expected standard deviations, and expected cross-security correlations. If the inputs are free of estimation error, mean-variance optimisation finds the efficient portfolio weights. However, because the inputs are statistical estimates (typically created by analysing historical data), they cannot be devoid of error. This inaccuracy will lead to over-investment in some asset classes and under-investment in others. For example, consider asset classes A and B, which differ only in that A's *true* expected return is slightly lower and its *true* standard deviation slightly higher than B's. The returns to assets A and B have identical correlations with the returns on each of the other assets under consideration for the portfolio. Asset B, the preferable asset of the two, would dominate A without estimation error. Even so, because of estimation error, asset A might have an *estimated* expected return that is higher and an *estimated* standard deviation that is lower than B's. In this case, optimiser-generated results will always select a higher portfolio weight for asset A than for B (Lummer & Riepe, 1994: 8).

Estimation error can also cause an efficient portfolio to appear inefficient. For example, Figure 4.1 shows a graph of the efficient frontier (the set of efficient portfolios for different levels of risk) and a portfolio P. Without estimation error, portfolio P is inefficient because it lies below the efficient frontier.

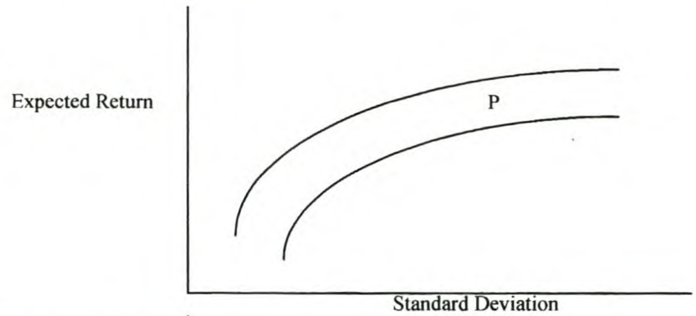
Figure 4.1: Efficient Frontier in the Absence of Estimation Error



Source: Lummer, S. L., Riepe, M. W., & Siegel, L. B. (1994). Taming your optimizer: A guide through the pitfalls of mean-variance optimisation, (9).

However, the presence of estimation error renders Figure 4.1 inadequate. Figure 4.2 is a more accurate description of reality. The true efficient frontier is somewhere within the band. This means that portfolio P may well be efficient. The width of the band is proportionate to the estimation error of the inputs. For example, the band widens as the expected return increases, because portfolios with low expected returns tend to be dominated by short-term fixed income securities for which mean-variance optimisation inputs are estimated with more confidence (Lummer & Riepe, 1994: 8).

Figure 4.2: Efficient Frontier with Estimation Error



Source: Lummer, S. L., Riepe, M. W., & Siegel, L. B. (1994). Taming your optimizer: A guide through the pitfalls of mean-variance optimisation, (9).

Lummer and Riepe (1994: 8) suggest limiting the impact of estimation error by using a constrained optimisation. The user sets the maximum or minimum allocation for a single asset or group of assets. Constraints are used to prevent assets with favourable inputs from dominating a portfolio to an extent that violates common sense.

A related problem with mean-variance optimisation is that its results can be unstable (small changes in inputs can result in large changes in portfolio contents) (Lummer & Riepe, 1994: 9). Black and Litterman (1991) constructed a global bond portfolio, where a mere change of 10 basis points in the expected return of German bonds (everything else remaining constant) changes the allocation of the German bonds from 0.0% to over 55.0% (Koskosidis & Duarte, 1997: 75). Lummer and Riepe (1994) suggest in order to minimise such dramatic changes in portfolio composition, sensitivity analysis can be used. This technique involves selecting an efficient portfolio and then altering the mean-variance inputs and seeing how close to efficient the portfolio is under the new set of inputs. The goal is to identify a set of asset class weights that will be close to efficient under several different sets of plausible inputs.

4.4 A Scenario-Based Approach to Asset Allocation

Lummer and Riepe (1994: 6) argue that optimisation will continue to play an important role in asset allocation in the future. But, whether or not it is mean-variance optimisation practised today, is another question.

As mentioned in the previous section, mean-variance optimisation does have its limitations. In the future, new and more robust models may be used to build upon mean-variance optimisation to reflect the ever-changing world markets. Scenario-based approaches to portfolio management, moving beyond the one period mean-variance model, and more economic foundations and risk analysis in investment management may be the solution in the foreseeable future. The objective of the scenario-based approach is to generate a representative set of plausible scenarios of future expected returns. The scenarios should realistically represent the probability of occurrence of possible events, and should capture the correlations among assets (Koskosidis & Duarte, 1997: 76).

Koskosidis and Duarte (1997) presents an optimisation-based asset allocation framework, which employs stochastic optimisation and scenario analysis to handle the uncertainties associated with forecasting the expected returns, volatilities, and cross-correlations of the assets. It also enables investors to incorporate their forward views on market expected returns in the optimisation process.

The model uses historical returns to create future return scenarios that capture the historical patterns of asset behaviour. By using multiple scenarios, the model preserves the diversity of asset behaviour, instead of flattening performance into some sort of aggregate average measurement like mean-variance optimisation. The model also provides the flexibility to overlay investors' forward views on the historical patterns, introducing forward expectation-based biases into the scenarios, if necessary.

This scenario-based analysis helps investors avoid the pitfalls associated with single-point forecasting, while it encompasses a wide variety of possible return outcomes so they can properly diversify their portfolios (Koskosidis & Duarte, 1997: 84).

4.4.1 Blending Investors' Views with Historical Patterns

Koskosidis and Duarte (1997) propose a framework that is intended to incorporate investors' views on expected returns into the asset allocation decision process. Black and Litterman (1991) describe a framework that allows investors to combine their views with historical information, based on the notion of a market equilibrium. Unfortunately, their study focuses on generating a single-point forecast. Thus, it suffers from the drawbacks associated with mean-variance optimisation (Koskosidis & Duarte, 1997: 80).

Koskosidis and Duarte's (1997) approach draw on the Black and Litterman concept in order to introduce future expectation-based biases in the scenarios. Every single historical scenario is modified according to investor views on the expected performance of each asset class. First, a set of scenarios based on historical patterns is generated. The scenarios are subsequently manipulated according to the views of the investor. The extent to which the scenarios are modified depends on the degree of confidence that one wants to attach to the investor views. The modified scenarios are then fed into the optimisation phase.

In more detail (Koskosidis & Duarte, 1997: 81):

1. "Expert" views on the expected returns of the assets are obtained from the investor.
2. Asset return scenarios based on historical patterns are generated.
3. A multivariate normal probability distribution of the past returns is generated, which is used to assign the appropriate weight (probability of occurrence) to each of the historical scenarios. This way, a stock market crash for example, will be included in the final set of scenarios, but it will get a small weight.
4. A statistical estimation process is used to tilt each historical multivariate distribution according to the investor views. The degree of modification depends on the degree of confidence that one wants to attach to these views. The final result is a new set of scenarios based on the historical patterns, which reflect, to a desired degree, the expectations of the investor on asset returns.
5. The modified scenarios along with their historical weights are fed into the optimisation model (stochastic network).

Koskosidis and Duarte (1997:81) describe the effect of the process using a simplified example. Consider two asset classes: three-month T-Bills and domestic large-capitalisation stocks. Historical scenarios are generated for the period January 1990 through June 1994 based on their monthly returns. During that period the average monthly excess return of the stock class over the three-month T-Bill was 0.08%, with a maximum and minimum of 10.78% and –10.10%. They assume that the investor's views on these asset classes for the next month are that the large-capitalisation stocks will outperform the three-month T-Bill by approximately 5.00%. Table 4.1 illustrates how the average, maximum, and minimum expected return scenarios change, as the historical scenarios are filtered through the investor's biases.

The changes show clearly how the degree of confidence directly affects the scenarios. When no confidence is assigned to the investor's views (first column), the historical scenarios remain unchanged. At the other extreme, when complete confidence is attached to the investor's views (last column), all the scenarios collapse into a single scenario, which are the investor's views. As the degree of confidence in "expert" views increases, the distribution of the scenarios moves away from the historical distribution and closer to the investor's views.

Table 4.1: Changes in Expected Return Scenarios after Combining Investor's Views with Historical Returns

Expected Excess Return Over U.S. T-Bill	Degree of Confidence in "Expert" Views: None	Very Little	Little	Neutral	Great	Very Great	Complete
Maximum	10.78%	10.71%	8.77%	6.39%	5.97%	5.04%	5.00%
Average	0.08%	0.10%	1.33%	3.70%	4.21%	4.89%	5.00%
Minimum	-10.10%	-10.03%	-6.19%	1.04%	2.68%	4.96%	5.00%

Source: Koskosidis, Y. A., & Duarte, A. M. (1997). A scenario-based approach to active asset allocation. Journal of Portfolio Management. 23(1), 82.

The advantage of using this approach is twofold (Koskosidis & Duarte, 1997: 82):

1. The asset allocation model can still use a set of expected return scenarios, instead of a single-point forecast (except in the case of complete confidence in investors' views).
2. This framework allows complete flexibility in terms of the degree of confidence assigned to investors' views.

4.5 Conclusion

The conceptual foundation of optimisers is solid and their use has greatly enhanced the portfolio management process, but mean-variance optimisation is complex, and prerequisites for understanding it include statistics, linear programming, and modern portfolio theory (Lummer, Riepe & Siegel, 1994: 9). In addition, it is difficult to use properly. Effective use of mean-variance optimisation in a practical setting requires an appreciation of its limitations. As described, estimating stable, long-term inputs for mean-variance optimisation will help to make the inherent limitations of mean-variance optimisation onerous (Lummer & Riepe, 1994: 23).

Future optimisation models, including scenario-based analysis, can be used to overcome the limitations of mean-variance optimisation (single-point forecasting). Instead of relying on a single scenario, investors can provide a set of plausible scenarios of future expected returns, and diversify their portfolio taking into consideration a larger number of potential return outcomes. The process allows much more flexibility. You can also use scenarios to structure portfolios that would encompass a wide variety of market conditions (Koskosidis & Duarte, 1997: 76).

4.6 Summary

- Strategic asset allocation is a fixed weight asset allocation strategy, or a set of asset class (stocks, bonds and cash) weights that can be used as a long-term guide for investing.

- The power of strategic asset allocation lies in its capacity to be tailored to the specific needs of the investor. For a diversified portfolio, selection of the asset mix – the strategic asset allocation decision – is an important determinant of long-term investment performance.

- Strategic asset allocation is based on three generally accepted assumptions:

  1. Risk and return go hand-in-hand in the capital markets;
  2. Capital markets are reasonably efficient over the long-term, at least in direction; and
  3. Market timing is not going to enhance the long-term investment results.

- The implication of the above assumptions is that any asset allocation model should take a long-term, strategic approach to asset allocation and any resulting portfolio should offer broad diversification among asset classes.

- In strategic asset allocation, no attempt whatsoever is made to predict short-term performance, or to change the asset mix to match current market conditions.

- Mean-variance optimisation has several important shortcomings that limit its effectiveness:

  1. Model solutions are often sensitive to changes in the inputs.
  2. The number of assets that can be included in the analysis is generally limited.
  3. Optimum asset allocations are only as good as the forecasts of prospective returns, risk, and correlation that go into the model.

- In the future, new and more robust models may be used to build upon mean-variance optimisation to reflect the ever-changing world markets.

- Scenario-based analysis provides the means to overcome the shortcomings of single-point forecasting. Instead of relying on a single scenario, investors can provide a set of plausible scenarios of future expected returns, and diversify their portfolio taking into consideration a larger number of potential return outcomes.

Chapter 5

Dynamic Asset Allocation

5.1 Introduction

Dynamic asset allocation refers to the allocation strategy that continually adjusts a portfolio's allocation in response to changing market conditions. It shifts the content of portfolios between two or more assets or asset classes in response to changes in the portfolio and/or external economic states, on a more-or-less continuous basis (Trippi & Harriff, 1991: 19).

5.2 Background

Most portfolios generally consist of risky assets. Fluctuations in the values of such assets will then cause the value of the portfolio in which they are held to change. The asset allocation of the portfolio will also change. One must decide how to rebalance the portfolio in response to such changes. Dynamic asset allocation strategies are explicit rules for doing so (Perold & Sharpe, 1995: 149).

Dynamic asset allocation can be created to suit specific investment objectives. It differs from static asset allocation in that trading in the assets occurs throughout the investment horizon, at times and in amounts that depend upon a fixed set of rules and unpredictable future events. It also assumes that the asset markets are continuous and liquid at all times (Trippi & Harriff, 1991: 19).

5.3 Characteristics of Dynamic Asset Allocation Strategies

Most dynamic asset allocation strategies can be classified according to six characteristics (Trippi & Harriff, 1991: 19):

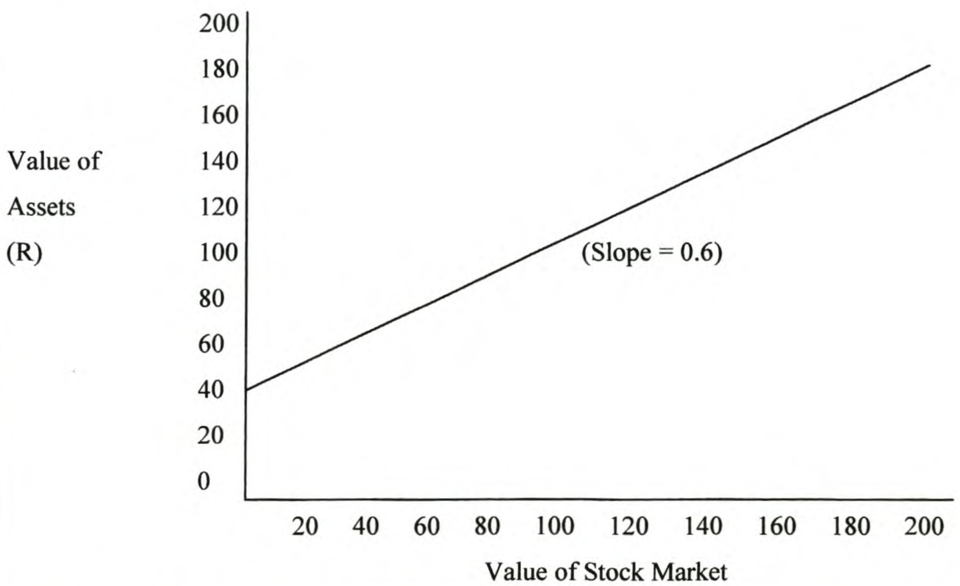
1. Determination of the desired mix of assets in the portfolio. Does the portfolio value, relative value of its components (internal), prices of one or more risky assets or indexes (external), or some other variable or combinations of the former determine the desired relative asset levels?

2. Continuity of the rebalance discipline. Is rebalancing continuous, or is it triggered only after some event or threshold is reached, or after a fixed adjustment interval? According to Perold and Sharpe (1995: 157), the answer depends not only on the rationale behind the choice of strategy, but also on the type of dynamic strategy chosen. Furthermore, it is important to be aware that the manner in which one resets the parameters of a dynamic strategy can dramatically alter its basic characteristics. Resetting rules should be considered an integral part of the dynamic strategy, and their effects explicitly should be taken into consideration.

3. Whether or not the strategy generally moves the portfolio into holding a greater proportion of its value in risky (or riskier) assets as their prices drop relative to risk free or less risky assets. Strategies that require systematic addition of equities to a portfolio are used to implement *concave* strategies. Concave strategies give rise to concave payoff curves, which increase at a decreasing rate as one moves from left to right. Strategies that result in *convex* payoff curves require the portfolio to include proportionately less of the risky asset when its price declines. Convex strategies give rise to convex payoff curves, which increase at an increasing rate as one moves from left to right. Figure 5.1 is an example

of how a payoff diagram for a 60/40 stock/T-Bill buy-and-hold strategy would look like. As mentioned above, a concave strategy gives rise to a concave payoff curve. Thus, the value of your assets increases at a decreasing rate as the stock market's value increase from left to right. Conversely, a convex strategy gives rise to convex payoff curves. Thus, the value of your assets increases at an increasing rate as the value of the stock market increases from left to right.

Figure 5.1: Payoff Diagram for 60/40 Stock-T-Bill Buy-and-Hold Strategy



Source: Perold, A. F., & Sharpe, W. F. (1995). Dynamic strategies for asset allocation. Financial Analyst Journal. 51(1), 150.

4. Degree of path dependence. *Path dependence* means that the terminal portfolio value does not only depend on the terminal market prices of the assets, but also on the history of price movements prior to the end of the investment horizon. *Path independence* means exactly the opposite.

5. Whether the strategy exhibits inherent hysteresis, or a lag in responding to changes in the price of the risky asset. The lag can take the form of overcoming some rebalancing threshold based on portfolio state, risky asset value, time, or some combination of the preceding.

6. Whether the strategy is most effective in achieving its goals in random or non-random markets of a particular type (e.g., those with a particular level of volatility or autocorrelation in the risky asset price series). Dynamic asset allocation strategies have advantages in both random and non-random markets. In random markets, dynamic asset allocation can be used to replicate many types of terminal return distributions, including those that would result from a combination of assets and options (Trippi & Harriff, 1991: 19).

5.4 Dynamic Strategies

Different strategies have different consequences in both the long term and short term. A certain dynamic strategy preferred by one type of investor may not be appropriate for another. The most popular and well-examined dynamic asset allocation strategy is portfolio insurance. Broadly speaking, portfolio insurance is any strategy that attempts to remove the downside risk faced by a portfolio (Lummer & Riepe, 1994: 3).

This strategy may be primarily geared to the institutional investor. As the portfolio loses value, the more risky assets are sold to buy assets that are risk free. On the other hand, as the market rises, less risky assets are sold and more risky investments are bought (Trippi & Harriff, 1991: 19). But, portfolio insurance is only one of many dynamic asset allocation strategies available to investors, depending on your specific investment objective.

This chapter discusses three very popular dynamic strategies, and show how the portfolio performs in bull, bear and flat markets, and in volatile and not-so-volatile markets. The focus will be on a choice between only two assets – stocks and the risk free asset (T-Bills). The concepts, however, are readily generalised to other asset classes (Perold & Sharpe, 1995: 149).

5.4.1 Constant-Mix Strategies

This strategy maintains an exposure to stocks that is a constant proportion of wealth. Investors who like this strategy have tolerances for risk that vary proportionately with their wealth. They will hold stocks at all wealth levels. This strategy is also referred to as "do something" strategies, because whenever the relative values of assets change, purchases and sales are required to return to the desired mix (Perold & Sharpe, 1995: 151).

For example, consider an investor who has put R60 in stocks and R40 in T-Bills, and wishes to maintain a 60/40 constant mix. Assume that the stock market declines by 10% (from 100 to 90). The investor's stocks are now worth R54, giving a total portfolio value of R94. At this point, the stock proportion is 57.4% (54/94) – well below the desired 60% level. To achieve the desired level, the portfolio must have 60% of R94, or R56.40, in stocks. Thus, the investor must purchase R2.40 (R56.40 – R54) of stocks, obtaining the money by selling a comparable amount of T-Bills (Perold & Sharpe, 1995: 151).

In general, rebalancing to a constant mix requires the purchase of stocks as they fall in value or the sale of stocks as they rise in value. Implementation of any dynamic strategy requires a rule concerning the conditions under which rebalancing will actually be undertaken. Transactions will be avoided until either the value of the portfolio or a portion of it (e.g., stocks) has changed by at least a given percentage (Perold & Sharpe, 1995: 151).

Table 5.1 shows what would happen if stocks fell from 100 to 90, then from 90 to 80, and so forth until they become worthless. Table 5.2 illustrates the more pleasant case in which stocks rise from 100 to 110, then from 110 to 120, and so forth. Figure 5.2 uses the results from Table 5.1 and Table 5.2 to produce a payoff diagram. For comparison, the line showing results for a 60/40 buy-and-hold strategy is also shown. The buy-and-hold strategy clearly dominates the constant-mix strategy. Whether the stock market goes up or down, the buy-and-hold investor has more money than the constant-mix investor (Perold & Sharpe, 1995: 151).

Table 5.1: Rebalancing to a Constant-Mix when Stock Value Falls

Case	Stock Market	Stock-Value	Bills-Value	Assets-Value	Stocks %
Initial	100	60.00	40.00	100.00	60.0%
After Change	90	54.00	40.00	94.00	57.4
After Rebalance	90	56.4	37.60	94.00	60.0
After Change	80	50.13	37.60	87.73	57.1
After Rebalance	80	52.64	35.09	87.73	60.0
After Change	70	46.06	35.09	81.15	56.8
After Rebalance	70	48.69	32.46	81.15	60.0
After Change	60	41.74	32.46	74.20	56.3
After Rebalance	60	44.52	29.68	74.20	60.0
After Change	50	37.10	29.68	66.78	55.6
After Rebalance	50	40.07	26.71	66.78	60.0
After Change	40	32.05	26.71	58.76	54.5
After Rebalance	40	35.26	23.51	58.76	60.0
After Change	30	26.44	23.51	49.95	52.9
After Rebalance	30	29.97	19.98	49.95	60.0
After Change	20	19.98	19.98	39.96	50.0
After Rebalance	20	23.98	15.98	39.96	60.0
After Change	10	11.99	15.98	27.97	42.9
After Rebalance	10	16.78	11.19	27.97	60.0
After Change	0	0.00	11.19	11.19	0.0
After Rebalance	0	6.71	4.48	11.19	60.0

Source: Perold, A. F., & Sharpe, W. F. (1995). Dynamic strategies for asset allocation. Financial Analyst Journal. 51(1), 152.

Table 5.2: Rebalancing to a Constant-Mix when Stock Value Rises

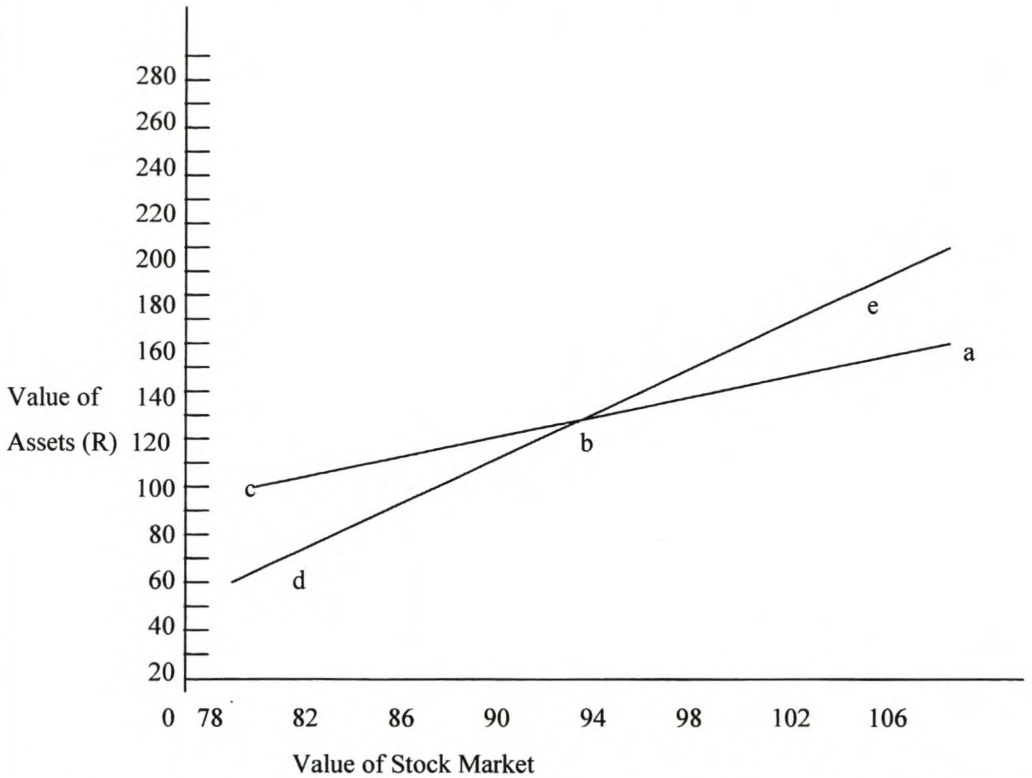
Case	Stock Market	Stock-Value	Bills-Value	Assets-Value	Stocks %
Initial	100	60.00	40.00	100.00	60.0%
After Change	110	66.00	40.00	106.00	62.3
After Rebalance	110	63.60	42.40	106.00	60.0
After Change	120	69.38	42.40	111.78	62.1
After Rebalance	120	67.07	44.71	111.78	60.0
After Change	130	72.66	44.71	117.37	61.9
After Rebalance	130	70.42	46.95	117.37	60.0
After Change	140	75.84	46.95	122.79	61.8
After Rebalance	140	73.67	49.12	122.79	60.0
After Change	150	78.94	49.12	128.05	61.6
After Rebalance	150	76.83	51.22	128.05	60.0
After Change	160	81.95	51.22	133.17	61.5
After Rebalance	160	79.90	53.27	133.17	60.0
After Change	170	84.90	53.27	138.17	61.4
After Rebalance	170	82.90	55.27	138.17	60.0
After Change	180	87.78	55.27	143.04	61.4
After Rebalance	180	85.83	57.22	143.04	60.0
After Change	190	90.59	57.22	147.81	61.3
After Rebalance	190	88.69	59.12	147.81	60.0
After Change	200	93.35	59.12	152.48	61.2
After Rebalance	200	91.49	60.99	152.48	60.0

Source: Perold, A. F., & Sharpe, W. F. (1995). Dynamic strategies for asset allocation. Financial Analyst Journal. 51(1), 152.

Why would anyone follow such a strategy then? One must consider other ways in which the stock market might move. In the examples above, once the stock market started moving, it kept moving in the same direction. The stock market is, however, capable of reversing itself, and such reversals favour constant-mix strategies over buy-and-bold strategies.

Consider a case in which stocks fall from 100 to 90, and then recover to 100. The market is flat, in the sense that it ends up where it started. In between, however, it oscillates back and forth. Thus, the effect of volatility is very important. For example, if the market is flat (i.e., goes down 10% and then moves up 10%), the simple buy-and-hold strategy will end up with the same wealth it had at the beginning.

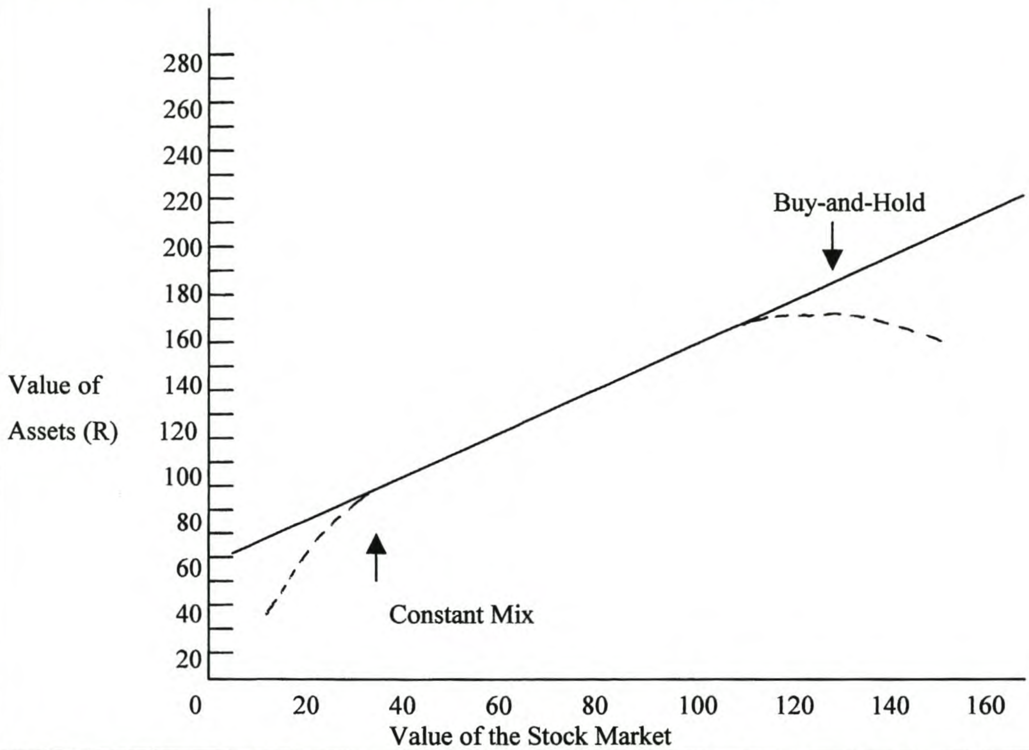
Figure 5.2: Payoff Diagram for 60/40 Constant-Mix and Buy-and-Hold Strategies



Source: Perold, A. F., & Sharpe, W. F. (1995). Dynamic strategies for asset allocation. <u>Financial Analyst Journal</u>. 51(1), 153.

The constant-mix investor will have more money due to the market, which oscillates back and forth. When the stock market falls from 100 to 90, the value of the investor's assets falls to R94. In Figure 5.3, this is shown by the line from point a to b (the number of shares of stock held in the portfolio determines the slope). For the buy-and-hold investor, further moves in the stock market will have proportionately similar effects. Thus, if the stock market falls to 80, the buy-and-hold investor's assets will fall to point c; if the market rises back to 100 (point a). A buy-and-hold investor simply travels up or down a single straight line in the payoff diagram (Perold & Sharpe, 1995: 152).

Figure 5.3: Payoff Diagram for 60/40 Constant-Mix Strategy



Source: Perold, A. F., & Sharpe, W. F. (1995). Dynamic strategies for asset allocation. Financial Analyst Journal. 51(1), 153.

This is not so for the constant-mix investor. Every rebalancing changes the number of shares of stock he holds, hence the slope of the line along which he will next travel in the payoff diagram. After a fall from point a to point b, he purchases more shares of stock. This increases the slope of the line. A further fall in the market to 80 will place the constant-mix investor at point d – below that of the buy-and-hold investor. But a subsequent rise in the market to 100 will place the constant-mix investor at point e – above the buy-and-hold investor. Who ultimately wins overall depends on the pattern the market moves (Perold & Sharpe, 1995: 153).

Thus, in general, constant-mix strategies will outperform buy-and-hold strategies in a flat (but oscillating) market because it trades in a way that exploits reversals.

Greater volatility (i.e., more and/or larger reversals) will emphasise this effect. Constant-mix strategies will under-perform buy-and-hold strategies when there are no reversals. This will also be the case in strong bull or bear markets, when reversals are small and relatively infrequent (Perold & Sharpe, 1995: 153).

The value of a constant-mix investor's assets after several rebalancing will depend on both the final level of the stock market, and on the manner in which stocks move from period to period before reaching that final level. Neither strategy (constant-mix; buy-and-hold) dominates the other. Thus, constant-mix strategies are superior if markets are characterised by reversals rather than trends, and buy-and-hold strategies are superior if there is a major move in one direction (Perold & Sharpe, 1995: 154).

5.4.2 Constant-Proportion Portfolio Insurance Strategies

Constant-proportion portfolio insurance (CPPI) strategies take the following form (Perold & Sharpe, 1995: 154):

$$\text{Rands in stock} = m\ (\text{Assets} - \text{Floor}),$$

Where m is a fixed multiplier greater than one.

To implement this CPPI strategy, the investor selects the multiplier and a floor below which he does not want the portfolio to fall. This floor grows at the same rate of return on T-Bills and must initially be less than total assets. The difference between assets and the floor could be like a "cushion". CPPI is simply trying to keep the exposure to stock a constant multiple of the cushion.

CPPI strategies have zero tolerance for risk (hence no exposure to stock) below a specified floor. Here the tolerance for risk increases more quickly above the floor than with buy-and-hold strategies (Perold & Sharpe, 1995: 154).

Example: Assume R100 of wealth, a floor of R75 and a multiplier (m) of two. Because the initial cushion is R25, the initial investment in stocks must be twice this, or R50. The initial mix is thus 50/50 for stocks/T-Bills.

If the stock market falls from 100 to 90, the investor's stocks will fall 10%, from R50 to R45. Total assets will then be R95, and the cushion will equal R20 (R95 – R75). According to the CPPI rule, the appropriate stock position is R40 (2 x R20). This requires the sale of R5 of stocks and the investment of the proceeds in T-Bills. If stocks continue to fall, more should be sold. If they increase in value, stocks should be bought (Perold & Sharpe, 1995: 154).

In stark contrast to constant-mix dynamic strategies, CPPI strategies sell stock as they fall and buy stock as they rise. This strategy, as well as any other dynamic asset allocation strategy, works best when prices do not jump and markets have sufficient liquidity. A price jump occurs when, for example, a stock trades at R100 per share and then R90 per share, with no opportunity for an investor to transact at an intermediate price (Lummer & Riepe, 1994: 6). Such a strategy puts more and more into the risk free asset (T-Bills) as stocks decline, reducing the exposure to stocks to zero as the assets approach the floor. In a bull market, this strategy will do very well (i.e., buying stocks as they rise). In a flat market, this strategy will do relatively poorly, owing to the same phenomenon that makes constant-mix strategies perform so well. Reversals hurt CPPI strategies because CPPI strategies sell on weakness only to see the market rebound, and buy on strength only to see the market weaken (Perold & Sharpe, 1995: 155).

Not one of the three strategies (buy-and-hold; constant-mix; CPPI) dominates the other. The winner or loser will be determined by the volatility, or lack of it, of the market.

5.4.3 Option-Based Portfolio Insurance Strategies

Option-based portfolio insurance (OBPI) strategies begin by specifying an investment horizon and a desired floor value at that horizon. OBPI strategies involve a floor value at every time prior to the horizon. Thus, if the horizon is one year and the floor at year-end is x, then the floor at any prior time is the present value of x. Once a floor is chosen and its present value calculated, the typical OBPI strategy consists of a set of strategies designed to give the same payoff at the horizon, as would a portfolio composed of T-Bills and call options (Perold & Sharpe, 1995: 156).

With OBPI strategies, the decision rule depends much on the time remaining before the horizon is reached. One instant prior to the horizon, OBPI strategies involve investing entirely in T-Bills if the assets equal the floor, and entirely in stocks if the assets exceed the floor (Perold & Sharpe, 1995: 157). It is important to note that the volatility of stock prices could create more and more trading, resulting in large transaction costs and rendering this strategy ineffective.

OBPI strategies sell stocks as they fall, and buy stocks as they rise. With a traditional OBPI strategy, for any given (positive) cushion, the exposure to stocks increases as time passes, reaching 100% of the asset value at the horizon. Such approaches are thus calendar-time dependent, which contrast with CPPI strategies, in which the exposure depends only on the size of the cushion (Perold & Sharpe, 1995: 157).

5.5 Concave versus Convex Strategies

Concave and convex strategies are very important. The basic shape of the payoff diagram is not so much dependent on the specific decision rule underlying the strategy, as it is on the kind of rebalancing required.

Strategies giving convex diagrams represent the purchase of portfolio insurance, while those giving concave diagrams represent its sale. Thus every buyer of a convex strategy is a seller of a concave strategy, and vice versa. The combination of the two is a buy-and-hold strategy. That convex and concave strategies are mirror images of one another indicates that the more demand there is for one of these strategies, the more costly its implementation will become (Perold & Sharpe, 1995: 156).

If growing numbers of investors switch to convex strategies, then markets will become more volatile, for there will be insufficient buyers in down markets and insufficient sellers in up markets at previously "fair" prices. In this setting, those following concave strategies may be rewarded. Conversely, if growing numbers switch to concave strategies, then the markets may become too stable. Prices may be too slow to adjust to fair economic value – thus rewarding for convex strategies. Generally the most popular strategy will subsidise the performance of the one that is least popular. Over time the market will move to a balance of the two (Perold & Sharpe, 1995: 156).

5.6 Summary

- Dynamic asset allocation refers to the allocation strategy that continually adjusts a portfolio's allocation in response to changing market conditions. It shifts the content of portfolios between two or more assets or asset classes in response to changes in the portfolio and/or external economic states, on a more-or-less continuous basis.

- Dynamic asset allocation differs from static asset allocation in that trading in the assets occurs throughout the investment horizon, at times and in amounts that depend upon a fixed set of rules and unpredictable future events.

- Dynamic asset allocation strategies can be used to:

  1. Limit downside risk;
  2. Exploit market imperfections; or
  3. Fine-tune the shape of the portfolio return probability distribution.

- "Do nothing" strategies (buy-and-hold) give payoff diagrams that are straight lines. "Buy stock as they fall, sell as they rise" strategies (constant-mix) give rise to concave payoff curves (which increase at a decreasing rate as one moves from left to right). That is, they tend not to have so much downside protection, and do relatively poorly in up markets. However, they do well in flat (but oscillating) markets. "Sell stocks as they fall, buy as they rise" strategies (CPPI & OBPI) give rise to convex payoff curves (which increase at an increasing rate). They tend to do poorly in flat (but oscillating) markets, but tend to give good downside protection and perform well in up markets (Perold & Sharpe, 1995: 156).

Chapter 6

Tactical Asset Allocation

6.1 Introduction

Tactical asset allocation is an active portfolio management strategy devised to reap the most benefits from shifting market conditions. This strategy principally attempts to overweight or underweight different asset classes (stocks, bonds or cash) at certain times to improve returns.

6.2 Background

Nairne (1994: 51) defines tactical asset allocation as a strategy that divides a portfolio among two or more asset groups, shifting the proportions allotted to each group according to short-term market predictions. This allocation strategy involves a periodic revision of the asset mix in order to improve returns, adjust for risk, or both. It definitely requires more time and effort in order to evaluate the economic environment, market conditions and specific investments.

A popular view of tactical asset allocation is that it is opportunistic in nature. It seeks to enhance investment returns through deliberate shifts away from the normal asset mix, as imposed by strategic asset allocation. The asset mix is adjusted in response to the shifting patterns of return available in the markets (Wise, 1994: 36). Tactical asset allocation managers thus shift their portfolios between stocks, bonds, and cash regularly in the hope of fleeing overvalued markets and concentrating in undervalued markets (Lappen, 1999: 168).

One consequence of tactical asset allocation, though, is that by over-weighting certain assets during certain times and under-weighting others, the portfolio could be riskier because of its reduced diversification. Therefore, the strategy would need to generate above market returns as compensation for this added risk.

6.3 The Rationale for Tactical Asset Allocation

Interest in tactical asset allocation grew when evidence of the forecast ability of stock and bond market returns appeared in the financial literature.[5] Tactical asset allocation strategies have also gained greatly in popularity ever since the stock market crash of 1987, because those following the strategy managed largely to avoid an over commitment to equities immediately before the crash (Brennan, Schwartz & Lagnado, 1997: 1377).

Although the statement above is highly controversial, Philips, Rogers, and Capaldi (1996) present some evidence of support. They show the potential advantage of tactical asset allocation by illustrating three hypothetical investment strategies:

1. Static Mix: Invest in a 60/40 stock bond (S&P 500/LBGC[6]) mixture, and rebalance the portfolio to its original proportions at the start of each month.

2. Perfect Foresight – Monthly Forecasts: At the start of each month, someone with perfect foresight tells the investor the better performing asset class (S&P 500/LBGC) for the coming month. Invest 100% of the portfolio in this asset class, and hold it for one month.

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[5] See Chapter 3

[6] LBGC – Lehman Brothers Government Corporate Bond Index

3. Perfect Foresight – Quarterly Forecasts: At the start of each quarter, someone with perfect foresight tells the investor the better performing asset class (S&P 500/LBGC) for the coming quarter. Invest 100% of the portfolio in this asset class, and hold it for one quarter.

The results of these three investment strategies over the period 1980 – 1994 are shown in Exhibit 6.1.

Exhibit 6.1: The Performance of Three Investment Strategies 1980 – 1994

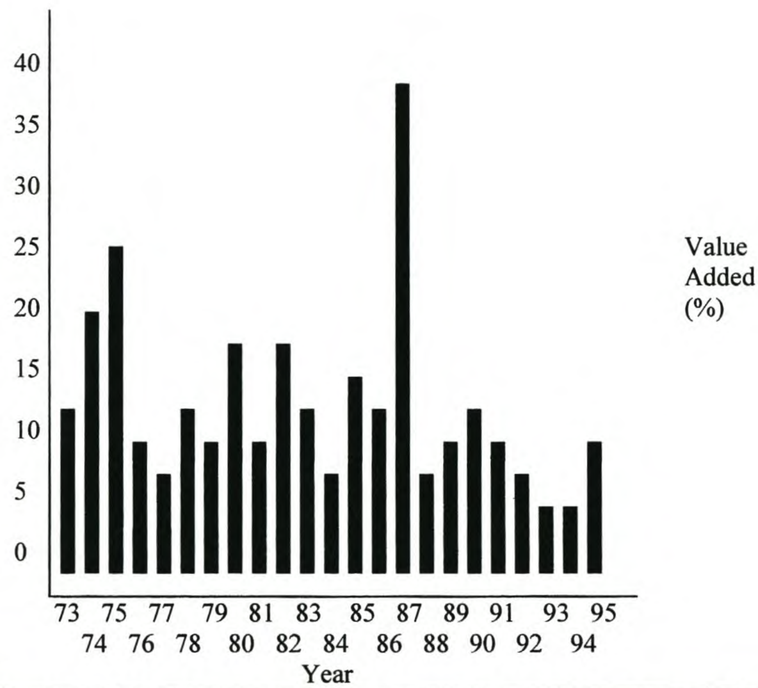
Strategy	Annualised Return (%)	Annualised Volatility (%)	Average Equity Exposure
Static Mix	13.28	10.43	0.60
Monthly Forecasts	35.21	10.56	0.57
Quarterly Forecasts	24.41	11.16	0.50

Source: Philips, T. K., Rogers, G. T., & Capaldi, R. E. (1996). Tactical asset allocation: 1977-1994. Journal of Portfolio Management. 23(1), 58.

The two tactical asset allocation strategies outperformed the static mix with three surprises. The *first* is the extent of the performance by the two tactical asset allocation strategies. The perfect monthly foresight strategy outperforms the static mix strategy by 22 percentage points per year, while the perfect quarterly foresight strategy outperforms the static mix strategy by 11 percentage points. The *second* is that the volatility of both tactical asset allocation strategies is little different from that of the static mix strategy. The large increase in return is thus achieved with little increase in risk. The *third* is that the average equity exposure of the tactical asset allocation strategies is less than that of the static mix strategy. Thus, these results cannot be explained by a higher equity exposure (Philips, Rogers, & Capaldi, 1996: 58).

Exhibit 6.2 shows the value added to a static 60/40 S&P 500/LBGC mixture in each calendar year since 1973.

Exhibit 6.2: Value Added to a 60/40 Static Portfolio by a Perfect Quarterly Foresight Strategy



Source: Philips, T. K., Rogers, G. T., & Capaldi, R. E. (1996). Tactical asset allocation: 1977-1994. Journal of Portfolio Management. 23(1), 60.

It is important to note that tactical asset allocation do sometimes find it difficult to add value to the portfolio. In Exhibit 6.2, the decline in value added in the post-crash period (1988 – 1994) is noticeable. The four worst years for tactical asset allocation over the twenty-three years (1988, 1992, 1993, and 1994) are all in the post-crash period. This all boils down to market conditions. Philips, Rogers, and Capaldi (1996: 63) found that the post-crash period mentioned above, displayed low volatility, high correlations among different asset classes, and similar returns from different asset classes. Stock prices rose from 1988 to 1990 even as bond yields rose, upsetting the historical relationship between fixed income and equity markets. The returns from stocks and bonds have been very similar from 1988 to 1990. These conditions made it difficult for the tactical asset allocation portfolio manager to add value.

6.4 Methods of Tactical Asset Allocation

6.4.1 Background

There are primarily two methods of tactical asset allocation, namely market timing and value based measures that are quantitatively derived. According to Larson and Wozniak (1995: 74), market timing entails shifting funds between asset classes, depending on the investor's perception of their short-term relative performance, absent any change in the investor's long-term attitude toward risk and return. This is much in the spirit of Philips, Rogers, and Capaldi's (1996) illustration of tactical asset allocation in the section above.

Quantitatively derived models shift in anticipation of a change in the relative price of one or more of the assets and do not make decisions by forecasting asset prices (Wise, 1994: 38). The asset mix signals are based on one or more relative, value based measures that are quantitatively derived, and are implemented expeditiously. Thus, they value markets on the basis of known measures, such as the yield on cash, the yield–to-maturity of long-term bonds and equity earnings yields (Gooding & Owens, 1993: 28). Although the difference between forecasting asset prices (market timing) and anticipating relative price changes (quantitative models) is not great, it is important to note that quantitative models rely on known value based measures, in contrast to attempts to predict the best performing asset class.

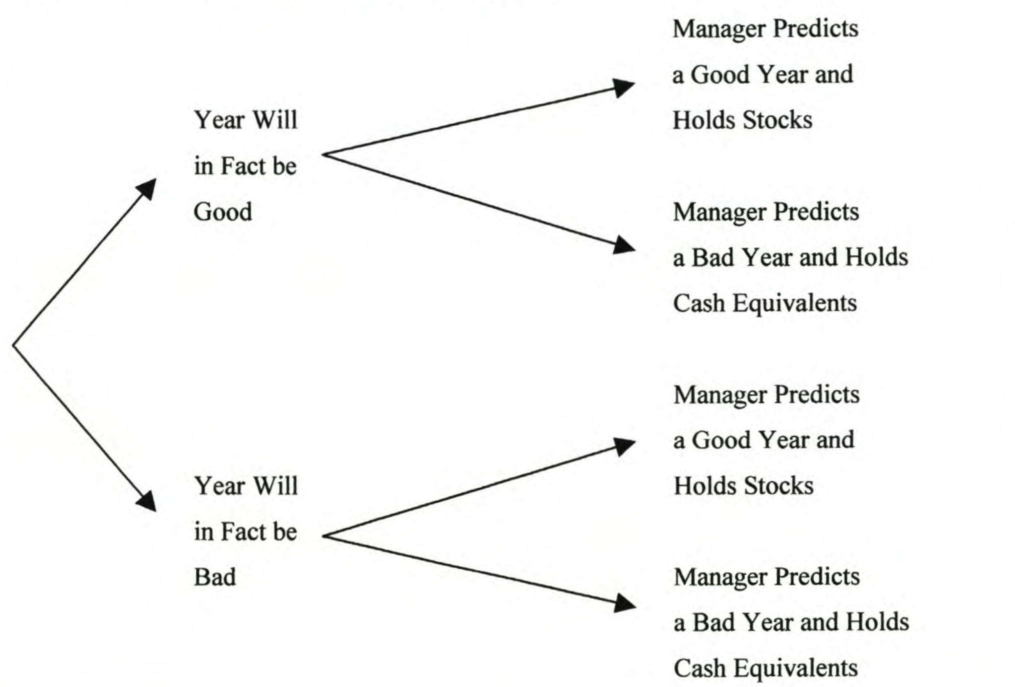
6.4.2 Market Timing

Tactical asset allocation's focus is on the changes in risk/return opportunities available from investments, which is much in the spirit of market timing strategies where the investor attempts to predict the best performing asset class. Successful market timing allows the investor to capture the upside returns from risky assets, while avoiding the potential for losses on the downside. Because stocks and bonds are more highly synchronized with each other than they are with risk free assets, there would be less incentive to transfer funds between stocks and bonds (Kritzman & Ryan, 1980: 45). Thus, market timing usually entails shifting funds between two asset classes – cash (considered as a risk free asset) and stock. An example of a straightforward market timing strategy would be to hold common stocks during bull markets and cash equivalents during bear markets (Sharpe, 1975: 60). Philips, Rogers, and Capaldi's (1996) example of tactical asset allocation is an excellent example of how market timing can add value to a portfolio.

Sharpe (1975) conducted the first and most often cited test of market timing. He explores the potential gains from market timing and shows how they relate to the manager's ability to make correct predictions. Annual total returns for cash equivalents (T-Bills) and stocks (S&P Composite Index) from 1929 to 1972 are used in the study. Each year is categorized as either a good or a bad stock market year. In a good year, the total return on stocks exceeds that on cash equivalents. In a bad year, the reverse holds. In terms of good and bad years, successful market timing can be defined as holding stocks in good years and cash equivalents in bad years.

Sharpe (1975: 61) first calculates the gains from perfect market timing and finds that 100% accurate market timing has two advantages. It gives returns that are both higher on average and subject to less variability. Perfect timing gave an average annual return of 14.86% per year from 1929 through 1972, while buying and holding stocks returned only 10.64% - a difference of 4.22% per year. The former policy brought less variable returns as well. The standard deviation of annual returns from perfect timing was 14.58% per year, as opposed to 21.06% per year from buying and holding stocks. Because it would be difficult to perfectly time the market each year, Sharpe also calculates the gains from less-than-perfect market timing. Figure 6.1 shows the assumed predictive process.

Figure 6.1: The Assumed Predictive Process



Source: Sharpe, W. F., (1975). Likely gains from market timing. Financial Analyst Journal. 31(2), 63.

Sharpe found that the proportion of good market years varied between 0.61 and 0.70 (See Table 6.1), and that the portfolio manager is assumed to be right only some of the time. His study indicates that at least a 70% accuracy rate in market timing is required to make the practice worthwhile. Because achieving a constant

70% or higher accuracy rate is unlikely, Sharpe's study suggests that the gains from market timing are likely to be modest at best, and that only a manager with truly superior predictive ability should even attempt to time the market.

Table 6.1: Performance During Good and Bad Years

Measure	'29-'72	'34-'72	'46-'72
Proportion of Good Years	0.61	0.67	0.70
Return on Cash Equivalents in Good Years			
Mean	2.21%	2.27%	2.92%
Standard Deviation	1.72	1.72	1.57
Return on Cash Equivalents in Bad Years			
Mean	2.66%	2.68%	4.10%
Standard Deviation	2.26	2.45	2.12
Return on Stocks in Good Years			
Mean	24.10%	22.99%	20.43%
Standard Deviation	12.98	11.90	11.83
Return on Stocks in Bad Years			
Mean	-10.74%	-7.70%	-5.35%
Standard Deviation	11.64	8.94	5.03

Source: Sharpe, W. F., (1975). Likely gains from market timing. Financial Analyst Journal. 31(2), 64.

Although Sharpe (1975) found that manager's forecasts are likely to be modest at best, and that only a manager with truly superior predictive ability should even attempt to time the market, Philips, Rogers and Capaldi (1996) reveal that manager's forecasts can be of value if they are highly accurate in extreme markets and less accurate in flat markets. The large gains from being right in extreme markets can outweigh the many small losses from being wrong in normal (flat) markets. Philips, Rogers & Capaldi's study (1996: 58) show that market-timing managers displayed significant timing skill in the earlier period of their study and that they displayed little or no timing skill in the latter period. Forecasts were highly accurate in extreme markets (crash of 1987) and less in flat markets (1988 to 1994). As mentioned previously, the post-crash period mentioned above, displayed low volatility, high correlations among different asset classes, and similar returns from different asset classes, which made it difficult for market timing to add value.

Because differences in asset class returns cannot be predicted with certainty on a monthly basis, Larson and Wozniak (1995), who present support for market timing, suggest that a two-month trend (sequential signal) in the predicted probabilities would give a better indication of the likelihood of differences in asset class returns in subsequent time periods. Larson & Wozniak (1995: 80) present support for the market timing argument based on empirical evidence. Results from a discrete regression model technique for market timing supports the argument that market timing can work in the real world. The study was conducted over a 15-year period, using the two-asset, common stock and cash equivalent portfolio choice. Significantly, Larson and Wozniak found a sequential signal from the discrete regression model ahead of the October 1987 crash, which can be regarded as empirical evidence of its usefulness. A similar sequential signal was observed prior to the August and September 1990 decline in the S&P 500 index.

6.5 Quantitatively Derived Tactical Asset Allocation Models

The common theme of these strategies is that an investor's equity allocation should be reduced (increased) as the market becomes overvalued (undervalued), with overvaluation (undervaluation) signalled by a low (high) dividend yield or a high (low) price/earnings ratio or price/book ratio (MacBeth & Emanuel, 1993: 30). Quantitatively derived tactical asset allocation models thus shift in anticipation of a change in the relative price of one or more of the assets and do not make decisions by forecasting asset prices (Wise, 1994: 38). The asset mix signals are based on one or more relative, value based measures that are quantitatively derived, and are implemented expeditiously. They value markets on the basis of known measures, such as the yield on cash, the yield–to-maturity of long-term bonds and equity earnings yields (Gooding & Owens, 1993: 28).

Quantitatively derived tactical asset allocation models are at its best during weak and turbulent markets. Contrarian by nature, these models seek out the asset classes promising to generate the highest risk-adjusted rates of return. The strategy favours markets that are least popular, and therefore most attractively priced, while avoiding markets when they are fashionable and therefore expensive. The contrarianism underlying the quantitatively derived tactical asset allocation models makes it an uncomfortable strategy, but the uncomfortable strategies are usually priced to offer superior rewards (Wise, 1994: 36).

According to Evnine and Henriksson (1987: 56), an investor's optimal asset mix will change as market conditions and opportunities change. Such changes could be the result of:

1. Changes in risk/return opportunities available from investments;
2. Changes in the investor's attitude toward risk; or
3. Changes in the investor's liability structure.

Quantitatively derived tactical asset allocation models' focus is on the changes in risk/return opportunities available from investments, which is much in the spirit of market timing strategies, where the investor attempts to predict the best performing asset class.

Benefits (adding value) from quantitatively derived tactical asset allocation models include (Gooding & Owens, 1993: 28):

1. *Relative Values:* Why should quantitatively derived tactical asset allocation add value above an unmanaged benchmark? First: Unlike most market timing methods, quantitative models are based on relative risk-adjusted valuation. When stocks or bonds become expensive or cheap relative to one another and to risk free cash equivalents, the quantitative model's process shifts the portfolio's asset mix away from the relative expensive asset into the relative cheap asset. The existence of overvaluations and market declines provides the tactical asset allocation strategy with actual times when value-based quantitatively derived tactical asset allocation processes should add value relative to static benchmark portfolios. Second: Quantitatively derived tactical asset allocation models usually consider the value trade-off between three or more asset classes, whereas market timing is predominately concerned with stocks and cash. It should be noted that including more assets may reduce risk, but also reduce return in the process.

2. *Market Extremes:* The reason that value-based quantitatively derived tactical asset allocation models should work is that market prices are sometimes driven to extremes during periods of undue optimism, for example the summer of 1987, and excessive pessimism, for example October 1987, during the market crash and over the next four to six weeks. Value-based quantitative tactical asset allocation models would have moved the portfolio away from overvalued assets (stocks in the summer of 1987) to undervalued ones (bonds or cash).

3. *Lower Transaction Costs:* One of the main causes for the underperformance of mutual funds or individual investor's portfolios to

static benchmark portfolios is transaction costs. Quantitative tactical asset allocation models are usually implemented with derivative securities or index funds, which means lower transaction costs than mutual funds or individual investors.

6.6 Summary

- Tactical asset allocation is an active portfolio management strategy, devised to reap the most benefits from shifting market conditions. This strategy principally attempts to overweight or underweight different asset classes (stocks, bonds or cash) at certain times to improve returns.

- Tactical asset allocation requires more time and effort in order to evaluate the economic environment, market conditions and specific investments.

- Tactical asset allocation's focus is on the changes in risk/return opportunities available from investments, which is much in the spirit of market timing strategies where the investor attempts to predict the best performing asset class.

- Tactical asset allocation, opportunistic in nature, is at its best during weak and turbulent markets. Contrarian by nature, tactical asset allocation seeks out the asset classes promising to generate the highest risk-adjusted rates of return.

- Most tactical asset allocation asset mix signals are based on one or more relative, value based measures that are quantitatively derived, and are implemented expeditiously.

- Tactical asset allocation must not be confused with market timing, which entails shifting funds between asset classes, depending on the investor's perception of their short-term relative performance, absent any change in the investor's long-term attitude toward risk and return.

Chapter 7

The Future of Asset Allocation

7.1 Introduction

> *"It has been said that portfolio management is the management of risk, not returns. Any asset allocation strategy will, of course, be constrained by real-world considerations"* (Arnott & von Germeten, 1983: 35)

Risk management will always be the primary objective of investment managers. To be more precise, the goals and importance of asset allocation will not change, but the mechanisms by which investors seek to achieve those goals will be new (Lummer & Riepe, 1994: 5).

7.2 The Future of Asset Allocation

Lummer and Riepe (1994: 5) divide most forecasters of the future of asset allocation into two camps. Forecasters in the first camp are eager to predict that the future will closely mirror the recent past. Forecasters in the second camp rely heavily upon the adage that the only constant is change itself. Globalisation and the integration of world economic markets could change the face of world markets, as we know it. As mentioned above, the goals and importance of asset allocation will, however, not change.

The goal of the asset allocation decision was, is, and will be to select a combination of assets that is intended, not necessarily to increase return, as much as it is to find the accepted rate of return while simultaneously reducing risk or maintaining it at a predefined level. Thus, there will always be an attempt to optimise the combination of investment returns and risk through asset allocation. This chapter predicts that asset allocation decisions, playing a large role in explaining asset returns today, will continue doing so in the future, but the mechanisms of implementing the asset allocation decision will be quite different, such as (Lummer & Riepe, 1994: 6):

1. Asset allocation strategies may assume certain market conditions that are not always present. For example, portfolio insurance strategies assume that the markets are continuous and liquid at all times. Thus, portfolio insurance strategies work best when prices do not jump[7] and markets have sufficient liquidity. These conditions were not present during the October 1987 crash. In the future, insurance strategies will be more adequately prepared to deal with certain types of market failure. Other asset allocation strategies will also have to be more adequately prepared to deal with these types of market adjustments or failures. Of course, future market failure and structures that should be implemented to avoid such failure need to be addressed.

2. Optimisation will continue to play an important role in asset allocation, but whether or not it is mean-variance optimisation as it is practised today is another question. Perhaps in the future a more practical model will be developed that incorporates more intuitive measures of risk, such as scenario-based approaches to portfolio management. In the future, new and more robust models may be used to build upon mean-variance optimisation to reflect the ever-changing world markets.

[7] A price jump occurs when, for example, a stock trades at R100 per share and then R90 per share, with no opportunity for an investor to transact at an intermediate price (Lummer & Riepe, 1994: 6).

Scenario-based approaches to portfolio management, moving beyond the one period mean-variance model, and more economic foundations and risk analysis in investment management may be the key to the foreseeable future.

7.3 Conclusion

There continues to be a need for investors and researchers to scrutinise the assumptions underlying today's models and evaluate whether the model is a sufficient reflection of reality.

Asset allocation remains more art than science and will probably remain so as long as the models used are but approximations of a reality that is in constant flux (Koskosidis & Duarte, 1997: 76). It is important to emphasise that any asset allocation model should be viewed as a tool to create portfolios in a rational and systematic way, based on investor views on the future behaviour of the markets under consideration. Undoubtedly, most of today's approaches will be found wanting in the future and new advances will be made (Lummer & Riepe, 1994: 6).

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