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FUNDAMENTAL INDEXATION AND MEAN REVERSION ON THE TAIWANESE EQUITY MARKET

BY

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This thesis is written under the sole supervision of Prof. Heng-Hsing Hsieh and submitted in full fulfillment of the requirements of a Masters Degree in Finance in the School of Business and Finance of the Faculty of Economic and Management Sciences at the University of the Western Cape.

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I

Declaration

I declare that this thesis, titled, *Fundamental Indexation and Mean Reversion on the Taiwanese Equity Market,* is my own work, that it has not been submitted for any degree or examination in any other university, and that all the sources I have used or quoted have been indicated and acknowledged by complete references.

Emmanuel C. Fongwa   **November 2015**

Sign:

UNIVERSITY *of the*
WESTERN CAPE

Dedication

I dedicate this thesis to the Fongwa family

Acknowledgements

With a humble heart, I express my sincere gratitude to my Lord and Saviour Jesus Christ in whom I live and move and have my being.

My profuse gratitude to my supervisor, Prof. Heng-Hsing Hsieh, for his undiscounted guidance, delightful insight and his believe in my potential despite my momentary and sometimes protracted lapses in judgment. His devotion to my success was unparalleled.

Without the unwavering support of my brother Dr. Neba Samuel Fongwa and my endearing sister Unice Fongwa, this thesis would be just a dream yet to be realised. They have been my co-pilots and I, forever, remain indebted to them in love.
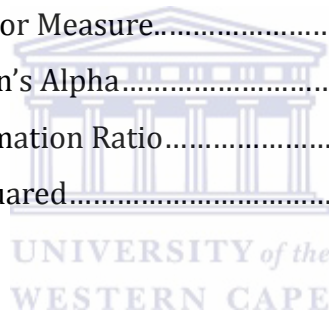
Many thanks to Pr/Dr Bertrand Sone and C.M.F.I. Cape Town for their incessant prayers and moral support throughout my studies. My deepest gratitude also goes to Dr. Mary Assim, Aunty Ida , Marc Assom, Wayne Small and other friends and family for all their invaluable input and constructive comments.

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ABSTRACT

The equity market has a long memory of indexing. The market portfolio is a cap-weighted index that weights stocks based on the market capitalisation of the stocks constituting the index and has been upheld by modern portfolio theory as the optimal portfolio, generating the highest return for given risk. Justification for the mean-variance efficiency of the market portfolio stems from the assumed efficiency of stock markets. However, Siegel (2006) states that, because of speculative trading in the market, which induces noise in stock prices, the prices of stocks deviate from their intrinsic value. The subsequent reversal of overweighting of overvalued stocks and underweighting of undervalued stocks to their intrinsic values by capitalisation weighting results in a return drag.

Recent observations of portfolios constructed based on weighting methodologies other than capitalisation weighting have resulted in portfolios that generate excess risk-adjusted returns over and above that of the market portfolio; casting doubt on the assumed efficiency of the market. One such weighting methodologies is fundamental indexation, under which stocks are weighted by their fundamental metrics of size. The concept was introduced by Arnott, Hsu and Moore (2005). Chen, Chen and Bassett (2007) also introduced the concept of smoothed cap weights (SCW) as a more reliable estimate of the intrinsic value of a stock.

This research study applies the concept of fundamental indexation and SCW to investigate the relative performance of fundamental indices of different concentrations (top 50 and mid-100 stocks) against cap-weighted portfolios on the Taiwanese equity market. The research period runs from January 2001 to June 2014, using the TEJ database as the data source. The TAIEX is employed as the market proxy. The research also examines the performance attribution and robustness of fundamental indices against cap-weighted portfolios. The results indicate that most fundamental indices constructed from the top 50 stocks are less mean-variance efficient than the TAIEX but more mean-variance efficient than the cap-weighted reference portfolio. All fundamental indices of the mid-100 stocks are more mean-variance efficient than the

TAIEX and the reference portfolio. The return drag observed in the cap-weighted TAIEX and reference portfolio evidences the presence of mean reversion of stocks.

Moreover, the returns of fundamental indices of the top 50 stocks are partly influenced by size risk premium but the fundamental indices comprised of the mid-100 stocks display return variations with statistically significant factor loading on the small cap (size) risk premium and value risk premium. Fundamental indices, on average show a higher resilience against the cap-weighted portfolios in both bull and bear markets. The sales index and fundamental composite index are the most mean-variance efficient fundamental indices and generate statistically significant alphas post accounting for both size and value risk premia.

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Chapter 1 INTRODUCTION

1.1   Preface

Capitalisation weighting (usually denoted as cap-weighting) is a weighting technique customarily associated with stock market indices. The technique entails determining the weight of stocks to be included in the index based on the proportion the stock bears, in terms of its market capitalisation, in relation to the total market capitalisation of the entire basket of stocks included in the index (Arnott & Shepherd, 2009). A stock market index, in simple terms, can be described as a tool employed by both market regulators and market participants to measure the value of a sector of the market. The sector could be limited to just an industry, an exchange, a country or, in certain instances, stretch across national boundaries. Stock market indices generally capture a predefined number of stocks constituting the largest stocks, usually determined by their market value, within the sector the index represents.

In 1896 Charles Dow introduced the first ever market index – The Dow Jones Industrial average – DJIA - (Stillman, 1986). With only 12 stocks at the time of inception (later expanding to 30), the index was an equally weighted index but in 1928 it switched to being a priced weighted index in order to fairly accommodate structural changes in company dynamics. The cap-weighted S&P 500 index was subsequently introduced in 1929 and was computed on a more frequent – daily - basis.

Although stock market indices may be hypothetical or just a mathematical construct, other investment vehicles called index funds, in an attempt to replicate the performance of the index, usually track them. This process is called benchmarking. The beauty of stock market indices lies in the fact that benchmarking against these indices exacts negligible costs from investors who choose to track them. Market indices are also a broad representation of the universe of all tradable stocks in the sector of the market represented by the index and the return to an investor tracking this index is the weighted return of all the stocks captured in the index.

The first index trust - the Vanguard 500 - was developed by Jack Bogle in 1976 and despite only sparingly being in favour at the time and, more so, subsequently derided for delivering meager/average returns, index trusts have grown exponentially and the mutual fund sector currently holds over thirty trillion in U.S. Dollars.

In spite of the early revelation of stock market indices, theoretical and empirical support for the concept only gained traction in the early 1950s. The genesis of the corroborative theory on stock market indices began in 1952, with the work of Harry Markowitz (1952; 1959) who set out to develop a mean-variance efficient portfolio of risky assets based on the mean return and variance of the assets, under the assumption of investor rationality and risk averseness. The model is based on deriving the portfolio that is tangent to the efficient frontier, called the market portfolio, and leveraging/deleveraging this portfolio with borrowing/investing from/in a risk-free asset at the risk-free rate. Sharpe (1964), Lintner (1965) and Black (1972) later extended the theory of Harry Markowitz (1952; 1959) into the capital asset pricing model (CAPM) based on the logic that the equilibrium expected return of an asset is not only a function of its variance but rather on the extent to which its returns co-vary with those of other assets. Therefore, Sharpe (1964) and Lintner (1965) assume the beta coefficient to be a positive and linear determinant of the return of a mean-variance efficient portfolio. While Black (1972) agrees with the positivity element of the beta with respect to returns, as suggested by Sharpe (1964) and Lintner (1965), he disagrees with the linearity assumption of their model.

Embedded within the CAPM is the efficient market hypothesis (EMH) of Fama (1970), which itself is built on the random walk theory of Kendall and Hill (1953), Samuelson (1965) and Mendelbrot (1966). Irrespective of the slightly different perspectives advanced by different researchers with respect to how efficiency in markets is perceived and the different degrees of efficiency - depending on the nature of the information in question - the basic tenet of the hypothesis rests on the premise that markets are efficient in terms of their speed and correctness in reflecting information about stock prices. Malkiel (2003) argues that even when markets make errors in valuation and prices are slightly amiss, that is, being a little too volatile vis-à-vis their fundamentals, markets are still a lot more efficient and less predictable as posited by the random walk

theory. Malkiel (2003) further alleges that because markets are efficient, it is impossible to earn above average returns without incurring above average risk.

Notwithstanding the unwavering belief in the efficiency of markets by its advocates, and the mean-variance efficiency of the market portfolio, substantial evidence has been exhumed depicting the market as less optimal. Mayers (1976) argues that for the market to be truly efficient all assets should be included in the market portfolio and Stambaugh (1982) tests a market portfolio inclusive of all assets and finds a breach in the risk-return relationship of the CAPM. Roll (1977) criticises the market portfolio for being unobservable.

The apparent weaknesses of the EMH and the CAPM rest on the flimsy assumptions on which they anchor; that is, assumptions that tend to be unrealistic in the real financial world. Amongst other criticisms, inefficiencies of the market have been demonstrated in terms of; assets exhibiting risk-return characteristics that violate predictions of the CAPM, predictable patterns in asset price movements and inefficiencies in the stock weighting methodology of the market portfolio. For instance, Basu (1977) finds that stocks with low price to earnings (P/E) ratios tend to have higher returns than predicted by the CAPM and vice versa. The size effect has also been investigated and proven by numerous researchers such as: Banz (1981); Reinganum (1981); Lakonishok and Shapiro (1986), whereby small size stocks, measured by market capitalisation, are found to generate higher risk-adjusted returns than large stocks. DeBondt and Thaler (1985) also discover the overreaction of stock prices to information and subsequent mean reversion of the prices. Jegadeesh and Titman (1993), on their end, uncover a short-term persistence in stock performance.

Rational, irrational and behavioural justifications have been provided as tentative explanations for the observed anomalies, with extended asset pricing models formulated to capture additional risk factors. For instance, the Fama-French (1993) 3-factor model and Carhart (1997) 4-factor model have been developed to this effect. However, evidence rebuffing the efficiency of the market has, at the very least, inspired misgivings in both financial market participants and researchers about just how efficient markets are.

The most recent blow to the advocates of market efficiency and the market portfolio was dealt by Arnott, Hsu and Moore (2005), in their inspiring paper on fundamental indexation, which is corroborated by the work of Siegel (2006), Hsu (2006) and Treynor (2005). Arnott et al. (2005) posit that the cap-weighted market portfolio underweights undervalued stocks while overweighting overvalued stocks and, therefore, results in a return drag when mean reversion of prices occur. Siegel (2006) provides reason for the faulty weighting in cap-weighted portfolios by postulating his noisy market hypothesis while Hsu (2006) and Treynor (2005) mathematically demonstrate how the return drag is brought about. Fundamental indexation has nonetheless encountered stiff criticism from skeptics such as Kaplan (2008) and Perold (2007), who declare that fundamental indexation is based on math and logic that is internally inconsistent while Asness (2006) says fundamental indexation is simply a repackaging of an active value investment strategy. In spite of the attacks on the concept of fundamental indexation, strong support and evidence of its superior performance has been unraveled across financial markets.

1.2 Background of the Market

Located roughly a hundred miles off the coast of Mainland China and Southwest of Japan, Taiwan is a small island, with a population of approximately 23.4 million inhabitants. The vagaries of revolutionary wars and upswings of anarchy have seen this territory, which once upon a time a province of China, evolve into an independent economy, with tremendous economic growth such that it was likened to being an economic powerhouse (Ammermann, 1999). Between 1624 and 1945, Taiwan experienced several transitions of occupational governments including the Chinese (with a breath of Soviet influence), Dutch and Spanish, Japanese and back to the Chinese governance before finally gaining independence in 1991, and subsequently holding its first ever presidential elections on March 23, 1996. The fight for power wreaked havoc across this geographical territory, with political and economic restrictions severely hampering its economic hatch (Ammermann 1999).

In the aftermath of disturbing ripples of power swings and regime change, Taiwan has, nevertheless, proven to be resilient, responsive, adaptive and successful in its domestic

as well as the global economic environment. The wake of economic growth in the late 40s was facilitated by the relaxation of long-standing restrictions on land sales and the blotting out of the feudalistic tenure system instituted by the Japanese occupational government. It was, however, not until the establishment of the Taiwan Stock Exchange that economic growth became exponential.

Although established in 1961, the Taiwan Stock Exchange (TWSE) only officially became operational on February 9, 1962 but the oversight committee – that is, Securities and Exchange Commission, SEC - was established a year prior [1960] to the TWSE in order to facilitate previous trading mechanisms operated via the land-to-the-tiller (LTT) program. The land reforms of 1953 between the Nationalist (KMT) and Communist (CCP) parties unveiled the inception of the Taiwan Stock Exchange market. Under the program, landowners or landholders traded their land or parts of it (transferring them to tenants) in exchange for shares in state-owned enterprises or government bonds (Yueh, 2009). The absence of a formal securities exchange presented challenges for the subsequent bondholders or shareholders who needed to liquidate their stakes to raise cash.

At the close of the year of inception of the Taiwan stock exchange corporation (TSEC) – that is, the parent company of the TWSE, also established in the same year as the TWSE -, only 18 firms were listed with a relatively much lower aggregate market capitalisation, as opposed to 809 listed companies in December 2013; with a total market capitalisation of NT$24,519,622 trillion. By December 2014, the total market capitalisation of the TWSE was estimated at NT$26,891,503 trillion. During the early years of operation of the TWSE, trading was restricted to the hours of 9 a.m. to midday on business days and 9 a.m. to 11 a.m. on weekends. Currently, normal trading is open from 9 a.m. to 5:30 p.m. and after-trading from 5:30 a.m. to 6 p.m. on all week days except Saturdays and Sundays.

Up until December 1983, direct trading on the TWSE by foreign firms and individuals was closed and all trading by non-domestic firms could only be done through one of four prescribed mutual funds. Ceilings to daily price movements and prohibitions/restrictions on short selling, options and futures were enforced by the

oversight committee. The limited trading hours, amongst other restrictions, would have been expected to hamper trading volumes and the growth of the total market capitalisation. On the contrary, trading volumes inflated geometrically and Taiwan wrestled with the top stock exchanges [Japan and USA) of the 1980s for largest market capitalisation and also became the world's third largest stock market in terms of trading volumes. Despite the relaxation of barriers to foreign direct trading on the TWSE in 1991, the inspiring growth of the aggregate market capitalisation of the TWSE had begun to take a nosedive in February 1990, eroding nearly 80% of the value of its market portfolio (TAIEX) – the Taiwan Stock Exchange Capitalisation Weighted Stock Index (Ammermann, 1999). According to the TWSE website, there has been a market capitalisation recovery of over 70% between 2008 and 2012.

[1]Figure 1.1: Taiwanese GDP and Market Capitalisation
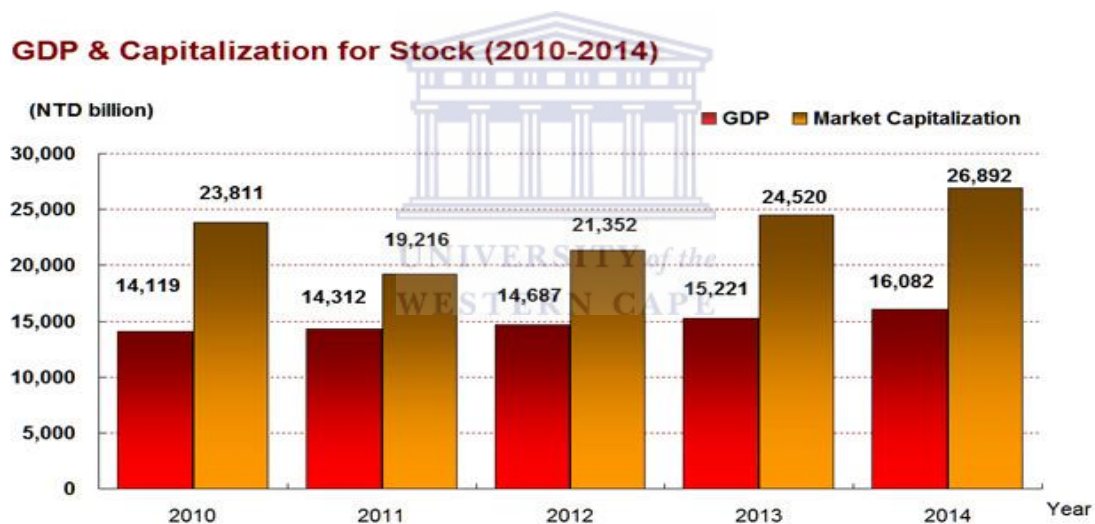
In 2011, a drop from almost NT$24 trillion to NT$19 trillion is observed but, overall, there was an upward trend in the growth of market capitalisation on the TWSE to NT$26.9 trillion at the end of 2014.

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[1]Figure 1.1 above displays the market capitalisation of the TWSE for the last five years. The data and table is sourced from the Taiwan stock exchange website.

1.3   Research Motivation

Although not classified as an emerging market by the International Monetary Fund (IMF) or the Emerging Markets Index, Taiwan is still maintained on the list of certain organisations, institutions or indices [Columbia University EMGP, FTSE, S&P, Dow Jones] as one, mostly on the basis of historicity or continuity; arguing that Taiwan had presumably developed past the emerging market phase and was being reviewed for a potential upgrade to the developed markets list. However, as of June 2014, Taiwan, together with South Korea, have been redefined by the global index provider's annual market classification review as emerging markets and retained on the MSCI index of emerging markets. The redefinition of Taiwan's market status is precipitated by the absence of meaningful improvements in key areas, which, in recent years, have adversely affected accessibility into its equity market (MSCI Press Release, 2014). According to the MSCI Press Release (2014), some of the prominent areas that have triggered the reclassification include but not limited to:

I.   The lack of an offshore currency market for the New Taiwan Dollar, resulting in limited currency convertibility.

II.   Hesitation to completely remove prefunding practices on the Taiwanese equity market.

III. The continued and rigid use of the ID system, perpetuating restrictions related to accessibility and identification of foreign investors. As a result of the stringent use of the ID system, in-kind transfers and off-exchange transactions have been rather difficult to execute.

On the basis of its renewed status as an emerging market and in comparison with other rather advanced emerging markets, the results of empirical studies on fundamental indexation on the Taiwanese market have been antithetical. Possibly, the recent developments that have provoked the reclassification of Taiwan as an emerging market might have also had an effect on this market's potential to benefit from fundamental indexation as suggested by Arnott and Shepherd (2009).

In the South African market, Ferreira and Krige (2011) have presented evidence, on a general basis, consonant with international findings, of the superiority of fundamental indexation over cap-weighted investing, especially in emerging markets. Although there

has not been any solo research on fundamental indexation performed on the Taiwan stock market, the work of Lobe and Walkshäusl (2008) on 50 developed and emerging countries (Taiwan inclusive), to be reviewed in chapter three, reveals that although fundamental indexation outperforms cap-weighted indices on a global basis and even in most individual markets, the fundamental composite index of Taiwan, together with three other countries (Columbia, Morocco and Venezuela), generates both a negative excess return (-2.07%) and a negative Sharpe ratio. This indicates an underperformance of fundamental indexation against capitalisation weighting. It is this rather bizarre result that incites interest into investigating this market further and finding possible explanations for this observation (should the results persist). Because noisy stocks are the raison d'être for return drag of cap-weighted indices, this research seeks to investigate whether fundamental indices constructed from differing fundamental attributes in Taiwan still exhibit a return drag. If so, this thesis analyses whether the return drag of fundamentally weighted indices in the Taiwanese equity market is indicative of a more mean-variance-efficient equity market or simply a misspecification/misvaluation of the fundamental variables or some other more subtle influence. If the findings prove otherwise, this research investigates the factors that have accounted for the reversal in return drag of the fundamental indices.

The revised status of Taiwan as an emerging market implies that noise levels in Taiwanese stock prices, as opposed to a developed equity market, are probably more pronounced as suggested by Arnott and Shepherd (2009). The inherent noise causes stock prices to diverge from their intrinsic values. Shiller (2005) states that there exists a tendency for things that go up a lot to come back down and for things that go down a lot to come back up. Siegel (2006) posits that the noise introduced into stock prices by irrational and speculative traders results to stock prices deviating from their intrinsic value. However, in his book, "stocks for the long run", Siegel (2007) demonstrates that stock prices have a tendency of clinging to a statistical trend line. That is, stock prices tend to revert to their mean. Hsu (2006) illustrates how the overweighting of stocks that have gone up a lot (overvalued) and underweighting of stocks that have gone done a lot (undervalued) creates a return drag in capitalisation weighting. Hsieh (2013) states that as long as mispricing in stocks is not persistent, mean reversion towards the intrinsic value of stocks will create a return drag in the performance of cap-weighted indices due

to misplaced assignment of weights to undervalued and overvalued stocks. Therefore, as long as mispricing is not permanent or extended the subsequent mean reversion of stock prices to their intrinsic values enables fundamental indexation to outperform cap-weighted indices. Based on the above implications, this research study also seeks to investigate degree of mean reversion in Taiwanese equity stock prices by examining how fundamental indices perform with respect to cap-weighted indices.

1.4   Problem Statement and Research objectives

Fundamental indexation, although a relatively recent weighting methodology, has proven to be empirically superior and financially beneficial to investors relative to its nemesis weighting methodology – capitalisation weighting. The findings have been amply documented by numerous researchers (Arnott, Hsu & Moore, 2005; Tamura and Shimizu, 2005; Hsieh, 2013). Its superiority across broad markets and time remains unquestioned but slight deviations from consensual expectations warrant further investigation.

The results from research performed by Lobe and Walkshäusl (2008) on 50 markets; Taiwan inclusive, reveal rather contrasting results. Without any misgivings as to the validity of the work of Lobe and Walkshäusl (2008), this research sets out to investigate why the findings of the Taiwanese equity market – a buoyant emerging market – are surprisingly divergent. Without any proclivity as to the preference of the expected findings, this research intends to perform an unbiased examination, using as reliable as possible data, with minimal biases possible, to either confirm prior findings of fundamental indexation on this market and subsequently provide reasonable explanations for observed results or, should the results differ, account for the divergence from prior findings.

Motivated by recent developments in the Taiwanese market – triggering a potential downgrade to emerging market status -, this research seeks to investigate if recent dynamics have rendered the market more susceptible to benefit from the perks associated with the application of fundamental indexation, as observed in other emerging economies.

In addition, this research also intends to compare the returns of a pure cap weighting to that of smoothed cap weighting as proposed by Chen, Chen and Bassett (2008). Smoothed cap weighting is based on finding the median of the cap weights within a fixed window of the immediate past. The purpose of this investigation is to determine if the application of the theory of mean reversion to stock investing provides a better weighting metric, than conventional cap weighting, for stock investing. If observed prices are an unbiased but rather noisy representation of the intrinsic value of a firm, then smoothing past prices for long-enough periods can provide an estimate of the true intrinsic value of the firm. Comparing the returns of the smoothed cap weights (SCW) with the returns of conventional cap weights further enlightens the broader research body as to the degree of noise inherent in conventional cap–weighting.

To put into perspective, the research problem is redefined by breaking it down into four key sub-questions; Q_1, Q_2, Q_3 and Q_4 as follows:

Q_1: Are fundamental indices, constructed from the Taiwanese top 50 and mid-100 stocks, more mean-variance efficient than cap-weighted indices?

Q_2: Does the smoothing of stock prices mitigate stock price volatility and, therefore, reduce the return drag inherent in cap-weighted indices as a result of speculative prices and misplaced weights?

Q_3: Is fundamental indexation a distinctive indexation methodology and are its returns statistically significantly influenced by style risks premia? If they are, do fundamental indices still generate positive alphas after accounting for style risks premia?

Q_4: Is the performance of fundamental indices more robust or resilient than that of cap-weighted indices in both bull and bear market cycles.

The above four sub-questions contextualise the research problem of this study. For subsequent discussions, the sub-questions contextualising the research problem will be viewed in the following light:

Q_1: Mean-variance efficiency of fundamental indices relative to cap-weighted portfolios.
Q_2: Relative performance of Smoothed Cap Weights.

Q3: Performance Attribution of fundamental indices.

Q4: Performance Robustness of fundamental indices.

In investigating the mean-variance efficiency of the fundamental indices, the mean-reversion of stock prices is also investigated. If the fundamental indices constructed in this research study turn out to be more mean-variance efficient than the cap-weighted indices, then mean reversion of stock prices is evidenced in the Taiwanese equity market. As discussed earlier the persistence of the superior performance of fundamental indices is partly engineered by the mean reversion of stock prices. As long as mispricing is not permanent, the subsequent mean reversion of stock prices to their intrinsic values enables fundamental indexation to outperform cap-weighted indices.

In an attempt to investigate the research problem of this research study, which examines the period from January 2001 to June 2014, the research objectives are defined below. Therefore, the research objectives of this thesis, which will subsequently be segmented in chapter four, are:

1. Construct fundamental indices from accounting variables constituting the top 50 stocks and the mid-100 stocks and comparative cap-weighted reference portfolios.

2. Construct a smoothed cap-weighted (SCW) index, based on the median prices of the top 50 and the mid-100 stocks.

3. Examine the return, risk and risk-adjusted returns of the indices constructed and perform a comparative analysis of the observed results.

4. Conduct performance attribution analysis on the returns of the fundamental indices based on the regression results of the CAPM and the Fama-French 3-factor model. The objective of performance attribution analysis is to determine the uniqueness of the fundamental indexation methodology by assessing the extent of value bias and small cap bias inherent in the performance of fundamental indices.

5. Perform a robustness analysis to determine if the performance of fundamental indices are more resilient than the cap-weighted indices in both bull and bear market cycles; defined under a dual system of market cycle determination.

The rationale for using only the top 50 or mid-100 stocks by market capitalisation is to align this research study with other indices on the Taiwanese market. Recently, the TSEC allied with the London Financial Times Stock Exchange – Footsie (FTSE) to form a joint index series called, "the FTSE TWSE (TSEC) Taiwan index series", composed of 2 benchmark indices (top 50 and mid-100) and 5 other sub-indices. The FTSE TWSE top 50 Taiwan index series is composed of the top 50 stocks by market capitalisation while the FTSE TWSE mid-100 Taiwan index series is composed of the next 100 stocks, ranked by market capitalisation. Because of the very high level of concentration in the Taiwanese stocks, the top 50 stocks, weighted by market capitalisation constitute between 50%-70% of the aggregate market capitalisation of the Taiwan equity market while the mid-100 stocks constitute about 20% of the aggregate market capitalisation. With respect to the fact that statistics for the performance of the cap-weighted FTSE TWSE Taiwan index series only became available in 2005 and the fundamental weighted FTSE TWSE RAFI Taiwan index series became available only in 2010, the performance of the indices constructed in this research are not evaluated against the TSEC benchmarks. This is to avoid comparing indices of different longevities, thereby clouding the objectivity of such an analysis.
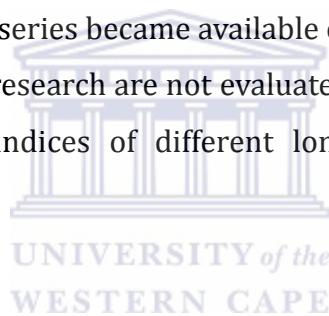
1.5 Overview

The period of this research runs from January 2001 to June 2014 and the research database is the Taiwan Economic Journal (TEJ), which, as of June 2014, was comprised of 1536 stocks. The motivation for this research is to assess whether the recent changes in the Taiwanese market, which have led to a reclassification of the market as an emerging market, have rendered the market more susceptible to tap into the benefits of fundamental indexation; with fundamental indices constructed from different metric attributes.

Chapter 2 of this research study discusses the theories underlying asset pricing models, as well as the asset pricing models themselves. Some market anomalies are also explained. Behavioural finance and the noisy market hypothesis are also explored. In chapter 3, empirical literature surrounding the concept of fundamental indexation is presented, followed by an examination of the benefits of fundamental indexation over

value investing. Chapter 4 recaps the research problem. It then proceeds to discuss the research sample, research data and the methodology, as well as research biases, and measures to mitigate the highlighted biases are explored.

Chapter 5 presents the results and analysis of the performance of fundamental indices and the cap-weighted indices for the different index concentrations while chapter 6 discusses the performance attribution of the fundamental indices using the regression results based on the CAPM and the Fama-French (1993) 3-factor model. Chapter 7 reviews the robustness of the results of the fundamental indices relative to the cap-weighted portfolios over the bear and bull phases of the market while chapter 8 presents a synopsis and conclusion of the research study, alongside, any limitations of this study and recommendations for future research.

1.6   Research Contribution

The major contribution of this research study is the perspective it provides on the impact of recent developments in the Taiwanese equity market on its susceptibility to benefit from the proven mean-variance efficiency of fundamental indexation. Prior to this research, and to the best knowledge of the researcher, only a single study on fundamental indexation has been performed on the TWSE by Lobe and Walkshäusl (2008). Although their findings reveal the underperformance of the fundamental composite index against the cap-weighted portfolio, recent developments, which have resulted in the reclassification of this market as an emerging market, might have rendered the market more inclined to benefit from the superior weighting methodology of fundamental indexation. Arnott and Shepherd (2009) reveal that emerging markets, due to the higher level of mispricing inherent in stocks, are more likely to tap into the benefits of fundamental indexation than developed markets. The findings of this research study, therefore, contribute to the existing body of evidence of the superior weighting methodology and mean-variance-efficiency of fundamental indexation vis-à-vis cap-weighting. The results also provide evidence to corroborate the work of Shiller (2005) and Siegel (2006) on mean reversion of stock prices, which tend to cause a drag in cap-weighted portfolios.

This research study improves on the research of Lobe and Walkshäusl (2008) in terms of the incorporating six additional years of recent data (July 2008 to June 2014), as well as constructing more fundamental indices using different size metrics. The investigation of the performance attribution using regression models also provides insight into what drives the performance of the fundamental indices.

Moreover, this research study also employs the innovative weighting methodology of Chen, Chen and Bassett (2007) using smoothed cap weights (SCW) to determine if smoothed share prices are a more appropriate reflection of the intrinsic value of the share. Because stock/share prices are considered more volatile relative to fundamental attributes like dividends (Siegel, 2007), smoothing the stock prices by finding the median stock price helps mitigate the volatility in prices, thereby reflecting a fairer value for the stock. The results of the application of the SWC in constructing fundamental indices contribute in enlightening the research community on whether or not smoothed prices are a better reflection of the intrinsic value of the share; judged on the basis of the relative performance of the SCW index against an unsmoothed cap-weighted index.

Chapter 2 THEORETICAL OVERVIEW

2.1   Introduction

The merit of any model is only as good as the theory and assumptions on which it rests. The finance community has proposed different models to be applied in the pricing of assets. Despite being established on different foundations - some relying on rational investor behaviour and efficient market conditions, while others attempt to employ cognitive factors and behavioural biases into the dynamics of asset pricing and decision making - each model or philosophy has proven to be relevant in its own respect and context, with neither being absolutely correct nor precisely wrong. Innocuous criticisms have been raised about the logic of the different models and savvy attempts made to improve on their reliability and relevance but the concept of asset pricing still remains a very fluid, if not elusive, construct in terms of its application, and more or less idiosyncratic.

This chapter discusses some of the most deliberated asset pricing models and philosophies, as well as the critiques and anomalies related to the models. Furthermore, recent developments aimed at providing possible explanations for observed deviations from prescribed market equilibrium behaviour and strategies for exploiting these lapses are discussed.

2.2   The Efficient Market Hypothesis and the Law of One Price

Because the price of an asset is invariably related to the return-risk expectations of the asset, modern portfolio theory (MPT) and asset-pricing models rely on the determination of such expected return-risk combinations, by the identification of factors that substantially contribute to the risk of a specific asset and the asset's sensitivity to such a factor. Furthermore, for such a return-risk trade off to be achieved with any degree of assurance, certain assumptions have to be made.

The leading assumptions of MPT are; the efficiency of the market (EMH) and the law of one price. The efficient market hypothesis, although originally developed by Fama (1970), has been hugely popularised by Malkiel (2003; 2005) and is largely associated with the random walk theory. Prior to discussing EMH and the law of one price, a

preliminary look at the random walk theory is necessary, as it is inherent in the discussion of EMH.

The random walk theory states that asset prices follow a random, unpredictable walk and prices of assets today are totally unrelated to tomorrow's prices. Prior to 1953, research on the random walk lacked rigor and most of the explanations revolved around the idea of "fair game" in the speculation of stock prices. That is, equal probabilities of gains or losses and an expected return of zero. Research on random walk only gained impetus when Kendall and Hill (1953) attempted to determine the serial correlation in the weekly changes in nineteen indices of British industrial share prices, as well as in spot prices for cotton and wheat, and found that the task of attempting to predict asset prices was nothing beyond a game of chance. A more plausible economic rationale for the random walk was provided by Samuelson (1965) and Mendelbrot (1966) when they examined futures contracts and showed that a futures price will follow a random walk if the price of such a contract at a certain time t is equal to the expected value at t of the spot price at the expiration of the contract. The absence of serial correlation in asset prices eventually led to the independence assumption, which translates into the concept that price movements are independent of one another and there exists little serial correlation between historical price movements sufficient to predict future patterns, based on which profitable investments can be made that outperform a simple buy and hold strategy.

The efficient market hypothesis (EMH), on the one hand, states that asset prices are unbiased estimates of the asset's true value. In an efficient market, asset prices fully reflect all available information about the asset. Therefore, if information flow to the market is uninhibited and rapid, prices will quickly respond to such information and because today's information is grossly unrelated to future information flows, future prices bear no resemblance, let alone, a predictable pattern, to past prices. In other words, history never repeats itself exactly. Fama (1970) defines the term "fully reflect" in terms of equilibrium prices. For prices to be at equilibrium, the expected return on an asset should be a function of the risk borne by the asset. With this understanding, investors in efficient markets do not seek to outperform the market but simply seek a return commensurate with the amount of risk undertaken.

The concept of efficient markets has experienced difficulties with the interpretation of the concept. Samuelson (1965) views efficiency as a state attained under conditions of perfect competition and zero transaction cost while Fama (1965) perceives efficiency as an actual outcome from the dealings of sophisticated traders in the market to minimise the distribution of actual prices from the expected/intrinsic value.

The tenets of EMH anchor on the belief that markets rapidly correct any mispricing of stocks, debarring the potential to exploit any arbitrage opportunities; at least, not in the long run. This injects some level of efficiency in markets but the nature of the information and speed at which it is made available to the market determines the relative level of efficiency. A breakdown of the different forms of market efficiency also facilitates the feasibility of testing EMH to determine the relative level of efficiency of any market.

A weak form efficient market is one where stock prices only reflect historical price information. In this kind of market, it is senseless to apply investment techniques, such as technical analysis, that seek to predict future patterns from past share price movements in order to benefit through the simultaneous/intermittent buying and selling of shares anticipated to experience increases or decreases in prices respectively. In a semi-strong form efficient market, stock prices reflect all publicly available information. Fundamental analysts who attempt to predict asset prices and volume data through analyses of price-earnings multiples, earnings per share and other published financial statement information only end up realising that their efforts are pointless. Empirical tests on the weak and semi-strong forms of market efficiency have generated contrasting results but, to a greater or lesser extent, most markets have been found to exhibit a certain degree of one of the first two forms of market efficiency. Finally, a strong form efficient market reflects all information, both public and private, in its asset prices. Therefore, in a strong form of the efficient market hypothesis, all efforts to utilise fundamental or technical analysis in order to identify undervalued stocks are rendered futile.

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The EMH does not however state that the price of an asset in an equilibrium market is always equal to its fundamental value but the theory insinuates that it is arduous, if not impossible, to handpick undervalued stocks or overvalued assets without costly analyses or an innate skill only possessed by a handful of investors (Siegel, 2006). Fama (1970) asserts that for market efficiency to hold, markets have to be frictionless, with the following conditions respected:

1) There are no transaction costs involved in the trading of securities;

2) Information is costless to all market participants; and

3) There is complete agreement amongst all investors about the implication of information for the current price and the distribution of future prices for the security.

These conditions are rather stringent and impractical in the real world and will definitely not be unanimously applicable to all investors but Fama (1970) posits that as long as a sufficient number of investors have access to available information, the efficiency of markets may still be preserved.

The law of one price, on the other hand, states that assets with self-same attributes, or the same asset trading in two different markets, should trade at the same price, indicative of the fact that prices are completely arbitraged, and it is therefore impossible to make riskless profits just by simply trading an asset short in one market and simultaneously trading the same asset long in another market. However, the ease of application of the law of one price varies with the nature of the product traded in the market. The law is much more applicable to financial markets (trading financial products) as opposed to consumer products because the presence of trademarks, inability to short sale consumer goods and difficulty in rapidly moving consumer products across international boundaries/markets, limits the enforcement of the law of one price, thereby creating gaps for the exploitation of arbitrage opportunities (Lamont & Thaler, 2003). With financial markets, however, the possibility of making near instantaneous buy and sell transactions across international markets, lower transaction costs, the rarity of perceived differences in asset attributes by investors, the practicability of short selling and the fact that the law itself is enforced by rational arbitrageurs themselves through their attempts at making riskless profits, renders the

relatively easy enforcement of this law feasible. For the law to hold, all investors do not need to be rational; only a substantial majority is required (Lamont & Thaler, 2003).

2.2.1   The Joint Hypothesis Problem.

Not only has the EMH experienced difficulties with arriving at a universal interpretation but finding a reliable statistical model to test the hypothesis has been equally problematic. Statistical models used to test the efficiency of markets rest on deriving expected returns, relative to risk changes, that are not significantly different from the actual return. The generation of alphas by the test model signals the efficacy of the model in predicting expected returns, on the basis of the factors employed by the model. Most of these statistical models, however, are based on the efficient market hypothesis (market equilibrium). Therefore, it is difficult to test the efficiency of markets using models that themselves rely on the tenets of market efficiency. Even if the model generates an alpha, it is impossible to tell whether the alpha is indicative of an inefficient market or a flawed model or both.

2.3   Modern Portfolio Theory (MPT)

The above-mentioned assumptions – EMH and the law of one price – are the capstones of traditional finance theory. Asset pricing models that draw inspiration from EMH and the law of one price are founded on MPT. MPT was pioneered by Harry Markowitz (1952) in his book, "Portfolio Selection". In his exploits, Markowitz (1952) offers a method for analysing the "suitability" of a portfolio based on the mean and variance of the constituent assets of the portfolio. By "suitability", the expected return of the portfolio is implied.

Markowitz's (1952) model assumes risk averseness by all investors, with convex loci of constant expected utility of wealth. Sharpe (1964) and Lintner (1965) introduce two new assumptions, being complete agreement by all investors of the joint distribution of returns, and borrowing and lending at the risk-free rate. Under the assumption of complete agreement on the joint distribution of asset returns, at a time t-1, investors select a risky portfolio with the expectation of generating or earning a stochastic return R_t at period t.

This implies;

$$R_t = (V_t / V_{t-1}) - 1 \qquad\qquad\qquad\qquad 2.1$$

Where:

R_t is the stochastic return at end of period t;

V_t is the value of the portfolio at period t; and

V_{t-1} is the value of the portfolio at the beginning of period t-1.

Figure 2.1 below depicts Markowitz's (1952) model. In line with the stipulations of the model, investors are only concerned with the mean and variance of their return within the single predetermined period. His model is based on the construction of an efficiently diversified portfolio, with the aim of identifying the north-westernmost portfolios in terms of expected returns and risk from the general population of securities (global feasible set).Based on the return and risk measure (volatility) of the risky portfolios, a minimum variance portfolio can be identified by plotting the global feasible set on a mean-variance diagram.
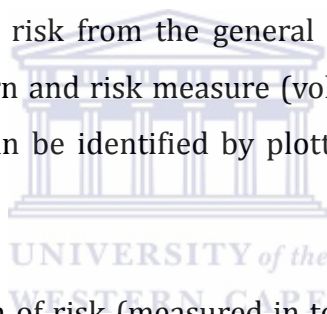
A line tracking the combination of risk (measured in terms of standard deviation) and expected return for all risky asset portfolios that seek to minimise risk for given return or maximise return for given risk produces an umbrella-shaped figure known as the minimum variance frontier. This resultant graph connecting all subsequent north-westernmost portfolios has been described by Merton (1972) as the efficient frontier and describes portfolios that generate the highest return for given levels of volatility. Clearly evident from Figure 2.1 is the trade-off between risk and return amongst the risky portfolios traced along the efficient frontier. For example, portfolios on the frontier to the right of "M" generate higher return but with greater risk while portfolio A, for instance, generates lower return at a relatively lower risk as shown in Figure 2.1 below.

In the absence of a risk-free asset, whereby borrowing and lending at the risk-free rate is not possible, only portfolios above the minimum variance portfolio (the portfolio on the efficient frontier with the smallest volatility), denoted MV, are mean-variance efficient. This is because any other portfolio below this minimum variance portfolio

generates a lower return for a given risk level. A risk-free asset is any asset that has a relatively short duration, has no default risk and is insensitive to interest rate fluctuations. In nominal terms, such an asset is devoid of any repayment risk (Giovannini, 2013).

Figure 2.1: Markowitz Efficient Frontier of Risky Assets
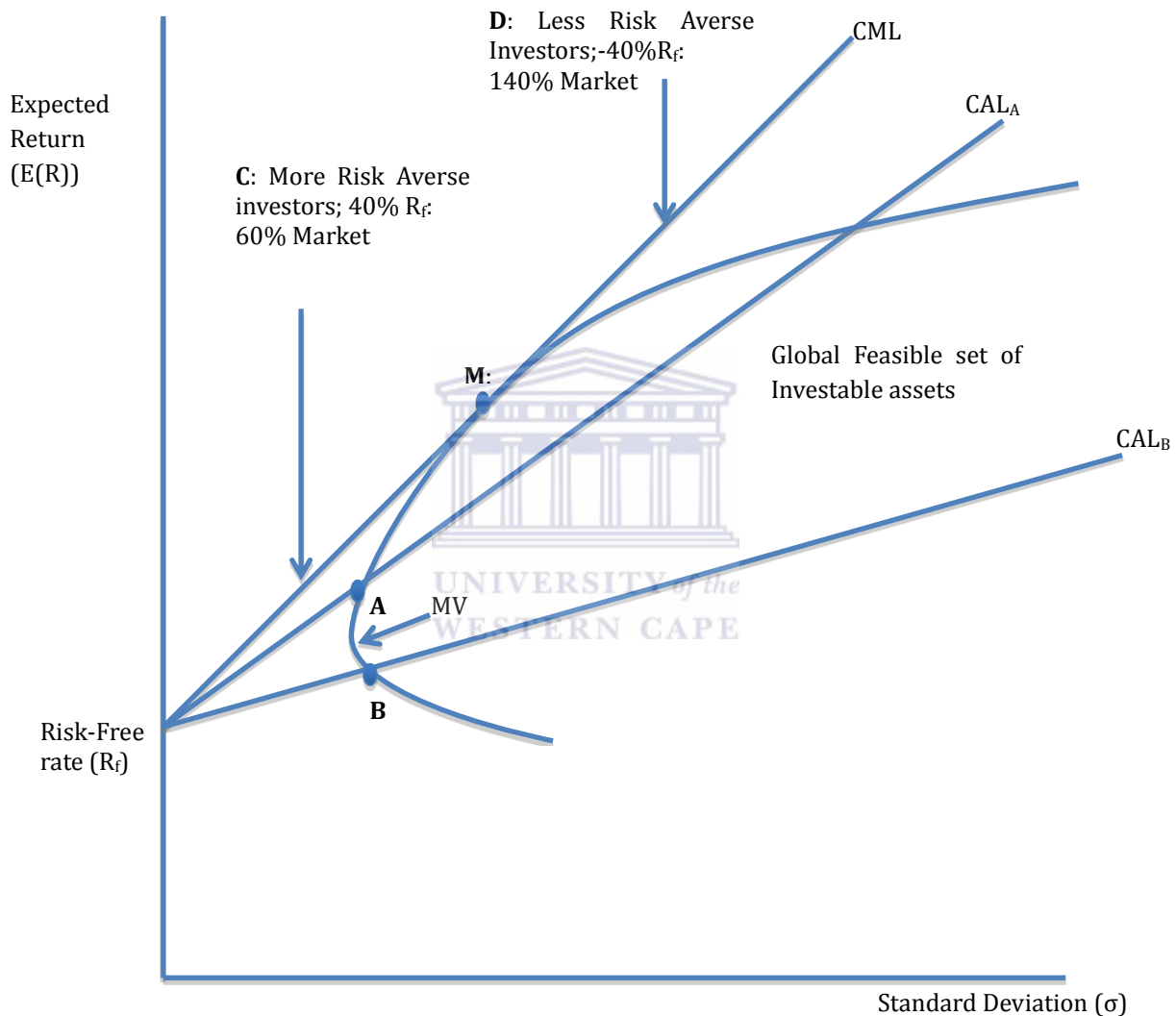
When a risk-free asset is introduced, combining these mean variance efficient portfolios with a risk-free asset results in straight lines called the capital allocation line (CAL$_A$ and CAL$_B$) as shown in Figure 2.1 above. The lines are straight because the risk-free rate has zero volatility and zero covariance with the risky assets. If this line is swung until it barely touches the efficient frontier at a point of tangency, the resultant CAL is called the capital market line (CML) and the point of tangency forms the tangency portfolio known

as the market portfolio, M. This portfolio is regarded as the optimal portfolio, from which maximum return is generated for given risk levels and all relevant risky assets are held in this portfolio in proportion to their respective weights, measured in terms of their market capitalisation. All risky assets not included in the market portfolio are devoid of demand and have no value thereof. The rational portfolio manager offers this optimal portfolio to all his clients with differences being only the degree of relative asset allocation that the client decides to make in the risk-free asset and the risky portfolio, depending on their degree of risk aversion. The determination of the optimal risky portfolio and the subsequent construction of the complete portfolio (that is, choosing one's point on the CML, based on risk preferences) together form what is referred to as separation property (Tobin, 1958). The market portfolio, M, as shown in Figure 2.1, is sufficiently capable of satisfying the investment demands of all investors and the holding of stocks in each individual investor's portfolio is in proportion to the holding of stocks in the market portfolio (Bodie, Kane & Marcus, 2007).

Although lying on the efficient frontier, subsequent to the introduction of the risk-free asset, portfolio A and B are nevertheless considered less efficient in terms of risk-return trade-off as they offer lower returns than a similar portfolio of comparable risk lying on the CML. In order to clearly depict the mechanism of risk-free lending and borrowing, investors who invest (lend) a certain proportion (x) in the risk-free asset, to earn a risk-free interest rate on that investment, can invest the remainder (1-x) of their wealth in the market portfolio, M, and earn the market return on this investment. Investors with greater risk aversion, denoted by C, invest the bulk of their wealth in the risk-free asset, R_f, while less risk averse investors invest the bulk of their investment in the market portfolio, M.

More risk seeking investors borrow a proportion (–x) at the risk-free rate and invest a proportion (1+x) in the market portfolio; such risk seeking investors are denoted by D in Figure 2.1. The difference in returns is only accounted for by the relative levels of risk undertaken by risk averse and risk seeking investors; not the inefficiency of the portfolio holding, as all portfolios along the CML are the most mean-variance efficient portfolios, as opposed to CAL_A and CAL_B.

The risk premium of the market portfolio is represented by the degree of risk aversion of an average investor and the standard deviation of the market, as depicted by Equation 2.2 below. Lower risk premiums instigate investors to move their investments to the risk-free asset while higher risk premiums act in just the opposite direction. This also implies that lower risk aversion results in lower risk premiums.

$$E(r_m) - r_f = A * \sigma_m \qquad\qquad 2.2$$

Where:

$E(r_m) - r_f$ is the risk premium of the market;

A   is the degree of risk aversion of the investor; and

σ_m is the standard deviation of the market.

The return to any investor who invests part of his wealth in the risk-free asset and the remainder in the market portfolio obtains a portfolio return given by

$$E(r_p) = r_f + \sigma_{fm} * \frac{E(r_m) - r_f}{\sigma_m} \qquad\qquad 2.3$$
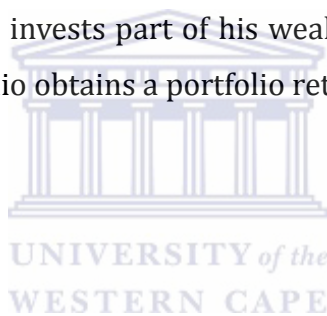
Where:

$E(r_p)$ is the expected return of the portfolio of one risky asset;

r_f is the risk-free rate;

σ_{fm} is the covariance of the market and the risk-free rate;

$E(r_m) - r_f$ is the risk premium of the market; and

σ_m is the standard deviation of the market.

In view of the fact that the risk-free rate has negligible variance, the covariance of the market and risk-free rate boils down to the variance of the market.

2.4 The Capital Asset Pricing Model (CAPM)

The capital asset pricing model was originally developed by Treynor (1962: 1963) but subsequent revisions were made to the model by Sharpe (1964), Lintner (1965) and Mossin (1966). The CAPM predicts the relationship between the risk and expected

return of risky assets. The model was further refined, mainly by most of its original developers, but the groundwork of the model was laid more than a decade earlier from the work of Harry Markowitz (1952; 1959) through his foray into the determination of the optimal risky portfolio, also known as the "market portfolio", as discussed above.

An important assumption in Equation 2.3 above is that the market portfolio only holds a single risky asset. However, the market portfolio is expected to hold more than just a single risky asset and investors are expected to invest part or all of their wealth in this market portfolio. The risk of the market portfolio as a whole is what bedevils the investor and not just the risk of an individual asset. Hence, the investor is interested in understanding the contribution each asset makes to the total risk of the portfolio. A well-diversified portfolio sheds off all individual asset risk (unsystematic risk). Only risk that cannot be diversified away (systematic risk) is relevant to the holder of the market portfolio. Unsystematic risks are risks that are unique to a particular asset and can be diversified away while systematic risk is risk that cannot be diversified away and, though affecting individual market participants at different levels, it, nevertheless, affects all market participants. Systematic risk cannot ordinarily be diversified away. The measure of this systematic risk of each individual stock (asset) is determined by the beta (β) coefficient and also indicates the asset's risk contribution to the market portfolio. Risk premiums on individual assets are also determined based on beta.

Due to complete agreement on the joint distribution of returns and the perception of the market portfolio as the optimal portfolio, with all investors distributing their wealth between the risk-free asset and the market portfolio, a shift in the measure of risk of each risky asset within the market portfolio becomes necessary. The standard deviation becomes less relevant as a measure of risk and the covariance risks of each asset in M relative to the covariance risks of other assets in M becomes more compelling as a better risk measure. This covariance risk measure is called the beta coefficient of the asset and the variance of the market portfolio is simply the weighted average of the betas of all its constituent risky assets and usually sums up to 1.

The CAPM seeks to predict a linear relationship between the expected return and systematic risk of assets as shown in Equation 2.4 below. However, the risk is measured

in terms of the beta coefficient of the asset.

$$E(r_i) = \alpha + r_f + \beta_i(E(r_m - r_f)) \hspace{6cm} 2.4$$

Where:

$E(r_i)$ is the expected return of the asset I;

r_f and r_m are the returns on the risk-free security (treasury bills) and market proxy respectively;

β_i is the beta of the asset I, representing the sensitivity of its returns to changes in the market risk premium; and

α represents the CAPM alpha.

The above expression implies that the expected return of an asset is a linear function of the product of its beta coefficient and the market risk premium ($E(r_m - r_f)$). So if markets are efficient and in equilibrium, plotting the expected return of assets against their betas should produce a linear graph with an intercept at the risk-free rate, R_f, and a gradient equal to the premium per unit of systematic risk measured by the beta coefficient. Figure 2.2 below illustrates this relationship.

Assets that plot above the SML, like "U", are deemed to be undervalued because they generate higher returns for given risk while assets plotting below the SML, such as "O", are perceived to be overvalued, generating lower returns for given risk. The rationale behind undervaluation and overvaluation stems from the fact that, based on the SML line, asset "U" is given a value of "E", and so is asset "O", but the true value of "U" is much greater than its estimated value on the basis of the CAPM formula. This makes asset "U" undervalued while asset "O" is perceived to have a value of "E" meanwhile its true value is much less than estimated, making it overvalued. The letter "M" denotes the market portfolio, and has a beta of 1, as previously alluded to.

The market portfolio weights its constituent risky assets by their market capitalisation and is considered a passive investment strategy since rebalancing is automated. Investors holding the market portfolio need not incur additional cost to reweight the assets in the portfolio, as the market automatically rebalances the assets based on the

revised market capitalisation of market portfolio constituents.

Figure 2.2: The Security Market Line (SML)
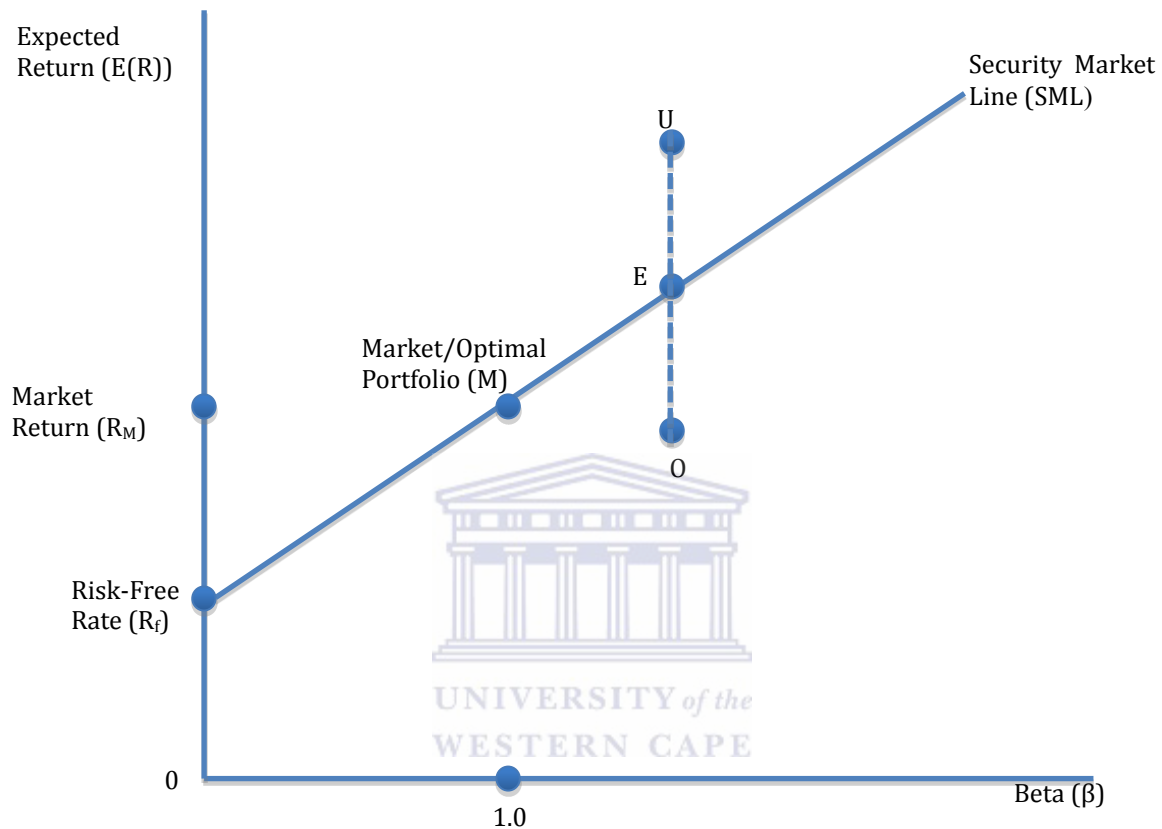
However, the EMH holds that active buying or selling of mispriced assets in order to restore price equilibrium erodes all temporary mispricing of assets. Undervalued assets (U) are bought, thereby increasing the demand, as well as bidding up the price of such assets until a fair value is reflected, meanwhile overvalued assets (O) are sold, consequently increasing the supply of such assets, thereby driving down price to an approximately fair value.

Despite the insightfulness of the CAPM, certain of its assumptions provoke more anxiety than provide solace for market participants. For instance, if rebalancing is automated and if active trading is a rather gross contravention of passive investing, then in the absence of such active trading, automatic stock price correction, as assumed by the CAPM, is in doubt. Again, should mispricing linger, the mean-variance efficient status of the market portfolio is also questioned. Moreover, the beta alone may not be sufficient to

proxy for all the possible risk factors that could affect or influence the expected return of a stock. Subsequent discussions will attempt to explore these issues in greater detail.

The theoretical failings and empirical challenges of the CAPM are rooted in its many simplifying assumptions such as; no taxes or transaction costs, unrestricted short selling, as well as unchecked borrowing and lending at the risk-free rate, homogeneity in expectations of all investors, one period investment horizon for all investors, and concern only for mean and variance of investments. These assumptions have been observed to be less tenuous or rather unrealistic in the real market environment and financial platforms. Real world constraints vis-à-vis the assumptions that lay the foundation of the CAPM create weak links in the veracity and efficacy of the model, making its profession of the mean-variance efficient status of the market portfolio a lot feebler, if not flawed.

Further critiques unearthed by Roll (1977) regarding the CAPM relate to the immeasurability, unobservability and ambiguity of the market portfolio. The hypothetical nature of the market portfolio makes it unclear as to exactly what assets should be included in its formation. As a result of the uncertain nature of this market portfolio, portfolios that approximate the basic tenet of the market portfolio, which is, mean-variance-efficiency, have been sought to proxy for the market portfolio. The heart of the ambiguity in determining the market portfolio, rest in the confusion of which assets should be included therein. Most market proxies use portfolios dominated by common stocks. But if the market portfolio, in consonance with its objective of being mean-variance-efficient, is assumed to include all relevant risky assets weighted by their market capitalisation, then other consumer goods, government bonds, as well as real estate assets and preferred stocks should be included therein to reflect the acclaimed comprehensiveness of the market portfolio. Mayers (1976) argues that a mean-variance efficient portfolio should include all risky assets and not just stocks. Stambaugh (1982), however, finds that the covariance of the risks and returns of the market portfolio is higher for risk and returns of U.S. common stocks than it is for alternative assets included in the determination of an expanded market portfolio.

2.5   Arbitrage Pricing Theory (APT)

Despite the criticisms of the CAPM, its persistence hitherto can be attributed to its compatibility with the generally acknowledged empirical regularity in asset returns; that is, their shared variability. Arbitrage asset pricing also shares this intuition but extends the model to include more than just a single factor, while maintaining the linear relationship of portfolio expected return and covariance of returns of priced risk factors. The model was exposited by Ross (1976) and modified by Huberman (1982) and anchors on the law of one price and the no arbitrage assumption. The no arbitrage assumption forms the basis of the notion of market equilibrium.

Although APT identifies itself with the prescriptions of portfolio diversification, it does not uphold any particular portfolio (as is the market portfolio in the CAPM model) as being mean-variance efficient and the model satisfies different investment horizons, as opposed to the single period horizon defined by the CAPM. APT decomposes the market risk developed in the CAPM into priced risk factors but sheds off most of the stringent and implausible assumptions of the CAPM, making the feasibility of its application more reasonable. The theory rests on the intuition that macroeconomic variables are somewhat endogenous to the pricing dynamics of assets. Only natural forces, such as earthquakes, are truly exogenous. Therefore any systematic macroeconomic variable that influences the price of an asset, to such an extent that additional diversification results in no added value for additional risks, the variable should be included as a constituent of the return determinants of that asset. The formularised expression of the theory is shown below:

$$E(r_i) = \alpha_i + \beta_{i1}R_1 + \beta_{i2}R_2 + \beta_{i3}R_3 + ... + \beta_{ij}R_j \qquad\qquad 2.3$$

Where:

$E(r_i)$ represents the expected return of asset i;

$R_1, R_2 ...R_j$ represent systematic macroeconomic variables that have idiosyncratic influences on the price/return of the asset i; and

$\beta_{i1,} \beta_{i2} ...\beta_{ij}$ represent the sensitivity of the returns of asset i to the returns of the identified priced risk, macroeconomic factors $R_1, R_2 ... R_j$.

Although these priced risk factors are not clearly identified in the empirical work, financial theory (Chen, Roll & Ross, 1986) suggests some macroeconomic factors that may offer explanatory power in the pricing of market assets. These factors include; long-term and short-term interest rate spreads, expected and unexpected inflation, the interest spread between high-grade and low-grade bonds, surprises in investor confidence and changes in industrial production. Roll and Ross (1980) stipulate that about three to five factors are generally sufficient to explain the returns of an asset.

2.6   Capital Market Anomalies

2.6.1   Anomalies

According to Ferreira (2008) an anomaly is a deviation from market equilibrium, which is not explained by the risk-return relationship predicted by the CAPM. These anomalies usually spring from the inefficiencies inherent in capital asset markets, creating risk-return patterns that violate the CAPM expectation. Some of the anomalies already observed in markets are discussed below

I)   Value Effect

The term "value" has typically been reserved for stocks exhibiting low price-earnings (PE) ratios and high earnings yield. Generally, stocks with high fundamental-to-market ratios are described as value stocks. Such fundamental-to-market ratios include book to market (B/M) ratio, sales to market ratio, earnings to market ratio and dividends to market ratio. Value effect relates to the historical observation of high B/M stocks outperforming low B/M (growth) stocks. The observation of this effect was initially made by Graham and Dodd (1940) but was publicised by the findings of research performed by Nicholson (1960). Further research by Basu (1975; 1977) and Ball (1978) on the U.S. market, Fama and French (1998) on the international market, Auret and Sinclaire (2006), and Hodnett, Hsieh and Van Rensburg (2012) on the South African market have confirmed the existence and persistence of value effect in stock returns. Hsieh (2013) also provides evidence of the existence of the value risk premium in sweetening the performance of most fundamental metric indices in emerging markets. While the unexplained alpha has been attributed to compensation for the possibly higher cash flow risk and financial risk inherent in value stocks as a result of their

smaller size, Malkiel (2009) criticises the logic of utilising B/M values altogether, arguing that such variables are fundamentally vulnerable to desirable tweaks by management.

II)   Size Effect

Evidence of the existence of this effect has been contradictory but nonetheless existent. The effect illustrates the alphas generated by small stocks over big stocks. As opposed to the term "small stocks" used in describing value stocks, which relate to stocks with high B/M ratios, the term "small stocks" in size effect relates to stocks with low market capitalisation. Banz (1981), over the period 1936-1975, performed lead research on this subject and his findings revealed that small cap stocks outperform large cap stocks by 19.8%. Although Lakonishok and Shapiro (1986) find no such evidence, Reinganum (1981), amongst other researchers, also discover evidence of the existence of size effect. Fama and French (1993), in developing their three-factor model, also investigate the size effect and find corroborating evidence of its existence. Switzer (2012) investigates the small cap effect on an international basis, especially in the G-7 countries and Middle-East North African (MENA) region. His findings reveal that small cap stocks in North America exhibit statistically significant excess returns. The excess return from stocks with low market capitalisation has been perceived as compensation for to the higher risk of lower tradability and inefficient information common to small stocks. Switzer (2012) finds that the risk factors associated with small cap portfolios vary from one country to another.

III)   Other Anomalies

Other anomalies include the momentum effect, which will be discussed further under the Carhart four-factor model. It relates to the positive autocorrelation between past and future stock prices. Contrary to the suggestion of Odean (1999) that momentum traders do not realise excess returns, evidence supporting this anomaly and its investment success has been overwhelming. Some of the researchers who have reported positive results on momentum effect include Jegadeesh and Titman (1993) on the U.S. market, Rouwenhorst (1998; 1999) on the European and Emerging markets and Hsieh, Hodnett and Van Rensburg (2012) on the South African market. Some momentum traders have, nonetheless, reported far worse performance than a simple buy and hold

strategy even when positive momentum was laid bare. Malkiel (2003) attributes the observed occasional underperformance of this strategy to the huge transaction cost inherent in its implementation.

Contrarian strategies on the other hand relate to negative autocorrelation between past and future prices. Contrarian strategies are founded on the overreaction and mean reversion hypothesis of DeBondt and Thaler (1985; 1987), whereby because investors are plagued by waves of pessimism and optimism, they eventually cause stock prices to deviate in a systematic manner. Upon regaining rational impetus, the stocks reverse to their mean values in the long run. Bildik and Gülay (2008) find that the application of a contrarian strategy on the Istanbul stock exchange generates statistically significant abnormal returns. Contrarily, Hossenbacus and Subadar (2010) discover that contrarian strategies generate negative abnormal returns on the stock exchange of Mauritius due to the "crowd" or herd behaviour of investors with respect to trading.

The January effect highlights the observation of higher risk-adjusted returns generated by stocks in the month of January relative to other months of the year. Amongst other researchers, Rozeff and Kinney (1976), Blume and Stambaugh (1983), Page and Way (1993) have documented evidence of the January effect. The Weekend effect refers to the observed truncation of Monday stock prices as a result of negative returns accumulated over the weekend, pursuant to large liquidation of long positions by traders who are reluctant to hold stocks over the uncertainties of the weekend. Rogalski (1984) provides convincing evidence of this effect on the U.S. market. Recent evidence on the prevalence of this anomaly is provided by Guler (2013) on emerging markets and Deyshappriya (2014) on the Sri Lankan stock exchange.

2.6.2   Possible Explanations of Market Anomalies

A.   **Methodological Biases**

In order to effectively test the efficiency of markets and, obviously, the efficacy of the CAPM, Fama (1970) insists on a joint test with an alternative expected return model. However, within any chosen sample period, expected return models often offer an incomplete characterisation of the average return patterns of stocks. Fama (1998) describes this challenge as a "bad-model problem". Bad-model problems are not only

limited to the chosen sample period but are aggravated by the length of the return window being investigated, and are particularly sensitive to empirical investigations of long-term buy-and-hold abnormal returns.

To compound the ails of models employed in methodologies aimed at uncovering anomalies, most of the models are far from being comprehensive and are only designed to capture return patterns for specific risk factors. Due to the vast number of metrics available to investigate the different spheres of anomalies, models are often restricted to only consider certain metrics in analytical tests. This, therefore, implies that the use of different models could inevitably lead to different results, with some revealing anomalies, while others might not. Even the use of the same model under different conditions could reveal antagonistic results (Fama, 1998). The problems highlighted with these models are closely related to some of the biases frequently encountered in research, such as; sample selection bias, time period bias and data mining bias.

B.   Rational Explanations

The rational explanations for capital market anomalies are also described as risk-based models because they attempt to capture the return variations in stocks by attributing the distribution and sensitivity of stock returns to style risks premia not captured by the CAPM.

I)   Fama and French (1993) 3-Factor Model

The CAPM predicts that the efficiency of markets and market equilibrium sifts away all abnormal returns, called alphas (α), such that any such α, within a well-diversified portfolio, should be a random, uncorrelated error term with an expected or average value of zero over a long observation period. The portfolio beta and market risk premium, under the CAPM, essentially account for any variability of portfolio returns. However, other priced risk factors have been found to account for abnormal returns that are unexplained by just the portfolio beta and market risk premium.

Amongst other researchers, DeBondt and Thaler (1985) reveal that investors have a tendency of extrapolating the performance of stocks based on past performance,

resulting in the overpricing of stocks that historically displayed a lower proportion of B/M ratios, to account for growth, while stocks displaying trending high B/M ratios being priced too low. By behaving in this way, investors are considered to overreact to perceived information conveyed by historical stock prices. The high B/M stocks (value stocks) are a priori considered to be those of small firms and prone to financial distress. The discounted pricing of these stocks is geared towards attempts to capture the increased risks inherent in these stocks. However, when investor overreaction is subsequently corrected (mean reversion), the overvalued growth stocks tend to underperform value stocks. These differences in returns result in alphas, which are not captured in the market return and are priced separately from market betas. Therefore, the returns of small cap stocks are observed to covary with those of other small firms while those of large cap stocks covarying with firms of a corresponding size, and not the typical market return and asset betas as stipulated by the CAPM.

In response to this observation, Fama and French (1993) develop a model that captures the higher average returns generated by both small cap stocks and high B/M stocks as priced risk factors. Fama and French (1993) posit that these factors propagate undiversifiable risks, and drive returns of stocks beyond the CAPM boundaries of the prescribed market portfolio returns and asset betas. The model is expressed in Equation 2.5 below.

$$E(R_{i,t}) - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,HML}(HML_t) + \beta_{i,SMB}(SMB_t) + \varepsilon_{i,t} \qquad 2.5$$

Where:

$\beta_{i,m}$ signifies the sensitivity of the excess returns of index i relative to the market risk premium;

$\beta_{i,HML}$ signifies the sensitivity of the returns of index i to movements in the value risk premium;

$\beta_{i,SMB}$ signifies the sensitivity of the returns of index i to movements in the size risk premium;

HML_t represents the excess return generated by stocks comprising the top 20th percentile weighted by B/M ratio (high book value) over stocks comprising the bottom 20th percentile by B/M ratios (low book value) from the sample;

SMB$_t$ represents the excess return generated by small-cap stocks (bottom 20th percentile) over large-cap stocks (top 20th percentile) from the sample;

α_i represents the Fama and French alpha; and

$\varepsilon_{i,t}$ Signifies the Fama-French regression residual.

The term "$E(R_{i,\,t})$ - $R_{f,\,t}$" signifies index i's excess return over the risk-free rate, and the multiple regression of $E(R_{i,\,t})$ - $R_{f,\,t}$ against the terms $R_{m,\,t}$ - $R_{f,\,t}$, HML$_t$ and SMB$_t$ produces slopes equal to their respective betas and an intercept equivalent to the Fama and French alpha.

The model assumes that, when portfolios are constructed on the basis of size, B/M ratios and other price-related variables, the model captures all return variations and the generated alpha is estimated to be random and approximately zero. However, subsequent research (Fama & French, 2004) by the authors of the model revealed that even when portfolios are constructed on the basis of price ratios such as B/M ratios, stocks with deeper cash flow pockets generate higher average returns that are not captured in the 3-factor model.

Although the systematic return explanatory variables (size and value) included in the three-factor model are not motivated by predictions of state variables commonly known to influence market returns, the variables, nevertheless, provide an explanatory power of the return dynamics of markets and asset portfolios.

II)   Carhart Four-Factor Model

Similar to the work of Fama and French (1993), which employed factors from previous research that could be systematic in determining the prices of assets, Carhart (1997) extend the work of Fama and French (1993) by supplementing their 3-factor model with a momentum factor. Short-term momentum simply implies that, in the short term, stock prices are more likely to drift in the same direction than otherwise. More specifically, stocks that have performed best over the past 3-12months will continue to do so over the subsequent 3-12months. The momentum effect, which was originally observed by Jegadeesh and Titman (1993), attempts to capture the cross-sectional return pattern of stocks by finding the difference in monthly returns of prior winner and prior loser stocks. The strategy is usually considered to be appropriate when making speedy

decisions about which stocks to invest in for the short term. While a precise reason cannot be attributed to this behaviour pattern of stock prices, possible explanations exist, including behavioural biases and higher return demands by momentum traders for the increased risk inherent in the strategy. The Carhart 4-factor model is shown below.

$$E(R_{i,t}) - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,HML}(HML_t) + \beta_{i,SMB}(SMB_t) + \beta_{i,UMD}(UMD_t) + \varepsilon \qquad 2.6$$

The only addition to the Fama and French (1993) 3-factor model in Equation 2.5 above, is the term $\beta_{i,UMD}(UMD_t)$.

Where:

UMD   signifies the return differential in the returns of recent prior winners, which went up and the returns of recent prior losers, which went down. That is, it represents the expected excess return generated by prior winners over losers; and

$\beta_{i,UMD}$ represents the sensitivity of the return of stock i to the excess return of prior winner stocks that went up over loser stocks that went down.

This model provides greater explanatory power than the previous models discussed, as it captures the alpha generated by the CAPM and the Fama and French (1993) 3-factor model, and also accounts for momentum, which, if present in stock return patterns, was not captured by its predecessors. Extended capital asset pricing models have purposely been developed to capture some of the previously unexplained return patterns of varying stock types. However, even the extended or augmented versions of the CAPM have failed to explain certain return deviations from their prescribed models. Amongst the deviations already explained by extended asset pricing models, some other anomalies are discussed in section 2.6 below.

C.   Irrational Explanations

The irrational explanations for anomalies anchor on determining patterns in stock price movements based on investor behaviour, as opposed to changes caused by the arrival of new information. Under irrational explanations, investors are considered to be less than

completely rational, contrary to predictions by advocates of MPT. Markets lack sufficient numbers of sophisticated traders, prescribed by Fama (1970) and traders tend to act in ways that result in suboptimal behaviour, resulting in stock return patterns that deviate from CAPM risk-return predictions. These behavioural patterns and theories underlying behavioural finance are discussed in the section below.

2.7   Behavioural Finance

The asset pricing models discussed above sprout from a common framework – the Rational Expected Equilibrium (REE) framework, which is subsumed in the broader theory of Expected Utility (EU). Expected utility theory was first introduced by [2]Bernoulli (1738) in his coin toss game called the "St. Petersburg paradox", where he discovered that the utility associated with a gamble is not necessarily tied to the absolute amount of the payoff but to the statistical expectations of the value the individual places on the outcomes of the gamble. Therefore, utility is not a linear function of wealth, nor is parallel to the expected value of the outcomes, but a concave evaluation of outcomes. Concavity of utility, under EU theory implies a decreasing marginal utility for all outcomes and all investors share a common utility function.

Under the REE framework, individual investor rationality, as well as consistent beliefs, is assumed. Consistent beliefs translates into the meaning of investors being rational in their decision-making processes in terms of rapidly updating their beliefs with recent information and upon having updated beliefs, make investment decisions that are normatively acceptable. However, past and recent investor behaviour has inflicted grave concerns about this assumed individual investor rationality. Deviations from the predictions of MPT and observations of consistent and persistent patterns in the generation of excess returns (alphas) not explained by asset pricing models, have resulted in the realisation that asset pricing theories founded on investor rationality and EMH provide unsatisfactory explanations of market return anomalies, or at least the total return generated by assets; be it from stock selection or investing strategies.

Behavioural finance attempts to provide alternative explanations of the mechanics of

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[2] The work of Bernoulli (1738) was eventually published in 2000 by Stearns

financial markets by relaxing some of the unrealistic assumptions of EU and REE. Contrary to EU, which rests on the assumption of risk aversion of all investors, behavioural finance presents a dichotomous pattern of behaviour towards gains and losses, as described by the prospects theory of Kahneman and Tversky (1979).

2.7.1   Prospects Theory

Prospects theory underlies behavioural finance and has certain overlaps with EU theory but is designed to explain investor behaviour under uncertainty. The theory was developed by Kahneman and Tversky (1979), who investigated the pattern of choice editing and evaluation – that is, how individuals go about making decisions. Contrary to an assumption of risk aversion throughout the utility function, Prospects theory employs a value function in its analysis of investor-risk-behaviour towards both gains and losses. Prospects theory posits that investors are risk averse in the region of gains and risk seeking in the region of losses. The differentiation of investor attitude towards gain and losses in prospects theory comes as a result of the failure of subjective EU theory in the most basic requirement of providing an accurate and reliable assessment of utilities, since utility might differ across individual investors for the same payoff matrix. That is, if individuals are asked to choose between a sure payoff of $50 and a probability of either having an equal chance of getting $200 or getting nothing, the choices of different individuals will differ in their utility preferences, because the value each individual places on a particular outcome determines his/her utility and might differ across a spectrum of decision makers, especially when losses are involved (McDermott, 2001). Prospects theory witfully addresses the difficulty of determining the precise utility of a particular investor by simply attempting to locate the region in which the investor lies on the value function and then a prediction of the likely behaviour or risk propensity of that investor can be made.

[3]Figure 2.3 below depicts the S-shaped value function of prospects theory. The function illustrates how subjective utility and choices are influenced by an investor's relative position. In addition, the S-shaped value function is defined in terms of gains and losses, pivoted at a reference point, and not with respect to absolute wealth.

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[3] Figure 2.3 is adapted from Kahneman and Tversky (1979) - Prospects Theory: An analysis of decision under risk.

Figure 2.3: S-Shaped Value Function of Prospects Theory
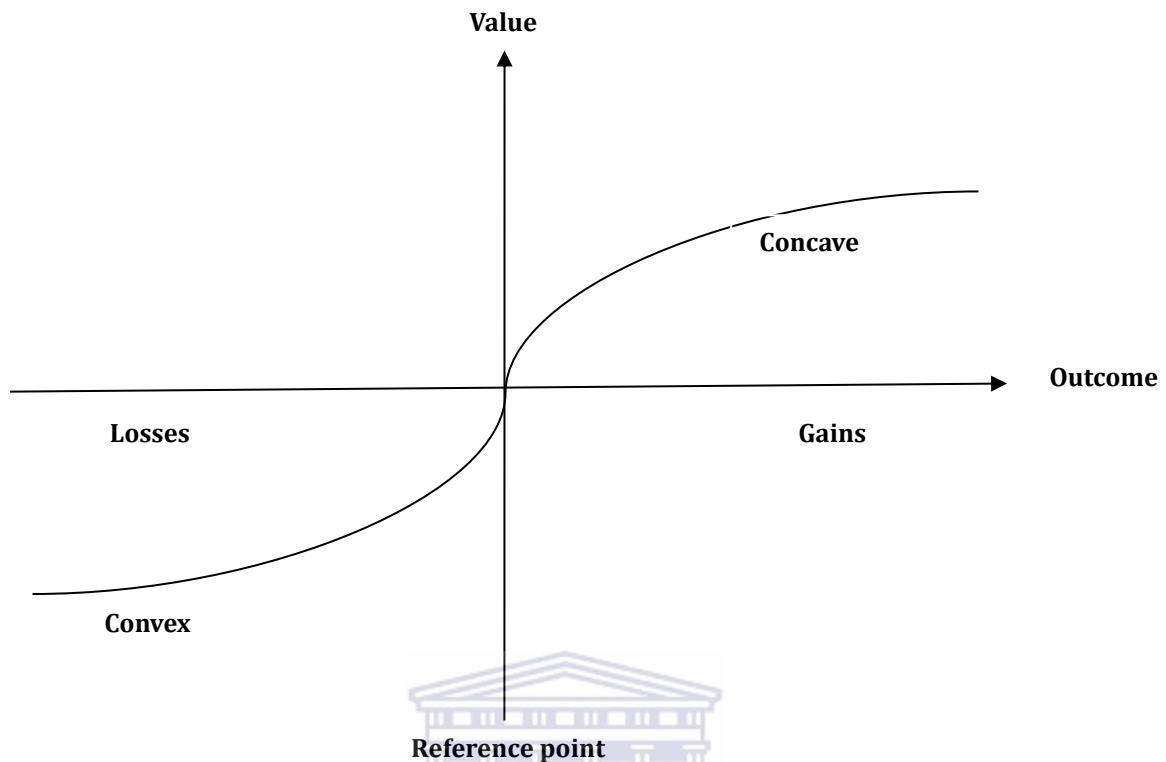
The value function is S-shaped; concave in the region of gains (signifying risk aversion) but convex in the region of losses (signifying risk seeking behaviour). In the domain of gains, investors experience decreasing marginal utility while experiencing decreasing marginal disutility for losses. The slope of the curve measures the sensitivity to change in utility. The reference point serves as the status quo of any individual and the slope is more sensitive close to the reference point than away. Furthermore, the slope is relatively steeper in the domain of loss than gains, implying that the pain from losing pinches more than happiness derived from comparative gains. This is described as loss aversion and individuals will rather maintain their status quo (reference point) than lose. Shefrin and Statman (1985) who further studied the loss aversion concept stipulate that loss aversion stems from ego and avoidance of regret by investors, who, most often than not, are seduced to retain losers for longer periods while selling off winners too soon.

[4]Figure 2.4 below clearly depicts the steepness of the slopes in the regions of gains and losses. The slope of the losses region is much steeper, as previously stated.

Figure 2.4: Depiction of Loss Aversion of the Value
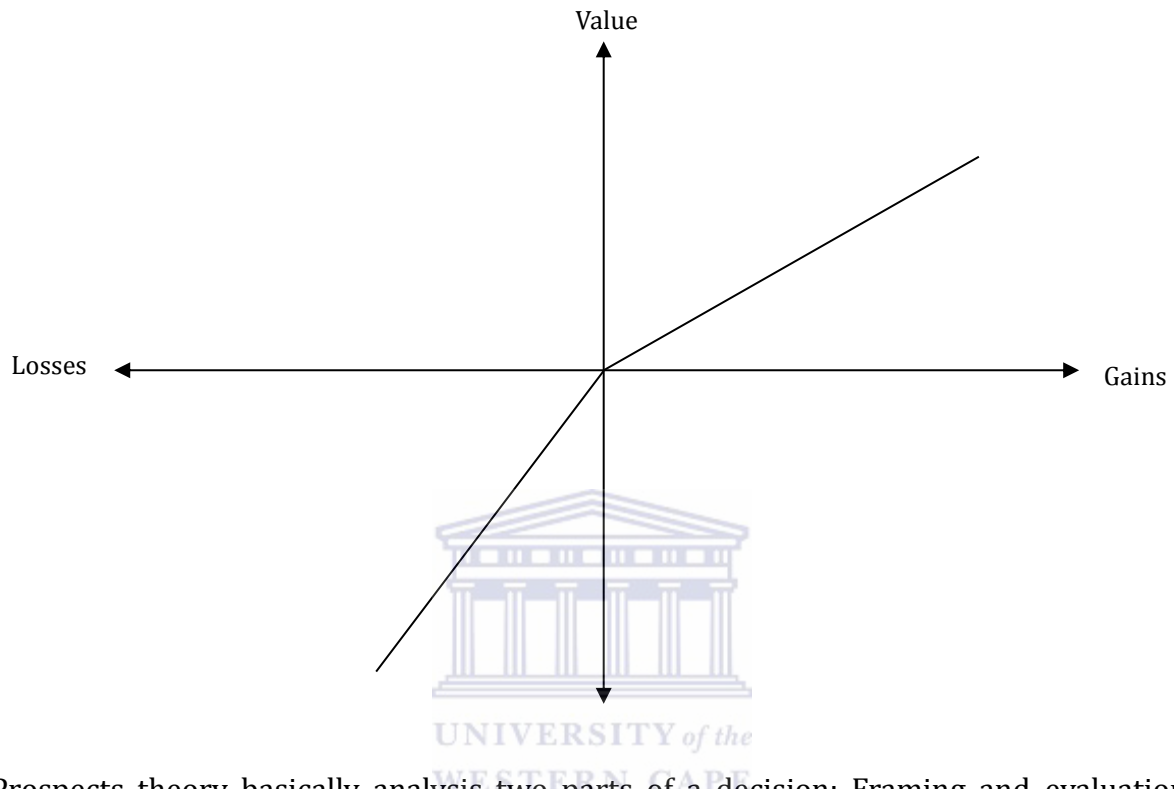
Prospects theory basically analysis two parts of a decision: Framing and evaluation. Framing is used to simplify the evaluation phase. The evaluation phase entails choosing between options while framing is the representation of outcomes, acts and contingencies associated with the options. In other words, framing is the process wherein the choice of an individual is influenced by the order or manner in which the options are presented. Innocuous manipulations in the way options are framed -such as, switching the order or merely using probabilities as opposed to absolute figures - evoke differing choices from individuals, despite the outcome being exactly the same. In framing decisions, a number of cognitive mechanisms or biases are employed by investors (McDermott, 2001).

Acceptance refers to the reluctance experienced by decision makers to reframe a particular construction of a choice problem once presented to them. Individuals often

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[4] Figure 2.4 is adapted from Kahneman and Tversky (1979) - Prospects Theory: An analysis of decision under risk.

regard the initial frame of options as reasonable and habour little misgivings as to its suitability. When presented with investment options, which are framed differently, even if the payoffs are similar, investors' choices tend to be influenced by the manner in which the decision options are presented (McDermott, 2001).

Segregation is evident in situations where individuals make decisions based on facts on the ground. Put differently, investors only consider the stipulated problem and factors directly relevant to the decision problem, without regard for the possibility of alternative outcomes or related factors that are not directly relevant (McDermott, 2001).

Coding relates to the proclivity of individuals to compartmentalise outcomes in terms of gains and losses. Investors always refer to their status quo or some other reference point in order to determine if their investment has generated gains or losses (Kahneman and Tversky, 1979). The absolute value of their wealth virtually plays no role in determining their utility. Sometimes the reference point used for comparison may not be rational but the comparative potential gain or loss relative to this reference point influences subsequent investment choices. Coding is somewhat related to anchorage in the sense that, in the determination of loss or gain, individuals anchor on their reference point; the reference point being their initial source of information (McDermott, 2001)

When individuals tend to synthesise the likelihood of choices that present identical outcomes, the behaviour is known as combination. On the other hand, when individuals analyse choices carrying the same outcome, such behaviour is called cancellation. With cancellation, individuals tend to ignore options that carry the same probability across different choice sets (McDermott, 2001).

Other heuristics and biases commonly observed to influence individual behaviour include:
Overconfidence; this is when individuals ascribe more credit to their competencies than is really worth. As a result of self-deception, individuals do not recognise and adjust for their limitations but make hasty and irrational decisions based on a misleading belief in their personal ability.
Omission bias; refers to the predilection to favour omissions as opposed to commissions

(Ritov and Baron, 1990). Because of loss aversion, investors prefer not to commit to courses of action that carry a probability of resulting in added losses, even if the omitted course of action could effectively shield them from the original loss. This is because investors perceive the action being omitted as too risky and could potentially add to their losses. For example, an investor may refuse to hedge because hedging is considered too risky and the loss from hedging more painful.

Heuristics simplification; which arises from the cognitive limitations of investors, who, in an attempt to simplify complex decisions, end up making suboptimal investment decisions (Hirshleifer, 2001). Investors, in making decision when limited information is available, employ availability heuristics. They rely on the information they have to shape their decisions. Some investors are conservative and underweight new information, while anchoring on, and adjusting, previous information to educate their decisions (Hirshleifer 2001).

Herd behaviour occurs when investors are either incapable of making rational decisions for themselves due to limited cognitive abilities or lack the necessary information for informed decision-making, and therefore rely on the judgment of another investor. A large community of investors resort to following a perceived rational investor, who, in reality, might not be as rational as predicted by EMH, thereby leading to a herd of irrational investors (McDermott, 2001). This behaviour is observed too often within the investing community.

2.8   The Noisy Market Hypothesis and Fundamental Indexation

2.8.1   The Noisy Market Hypothesis

EMH, which forms the basis of MPT, predicts the market portfolio as the mean-variance efficient portfolio – generating the highest possible return for given risk. The market portfolio is cap-weighted, weighting each asset according to its share of market capitalisation relative to the aggregate market value of all assets included in the market portfolio. Therefore, simply buying and holding a proportion of the market portfolio or a proxy of the market portfolio guarantees a superior investment strategy. For the mean-variance-efficient condition to hold, the efficiency of the market should be unquestioned

and prices should correctly or approximately reflect the fair value of all assets. Therefore, if assets are fairly priced, then upon applying Achille's heel of capitalisation weighting, as described by Arnott, Hsu & West (2008), whereby a greater proportion of investments is made in high-flying (growth) stocks because they are trading at premium multiples, such stocks should generate returns that do not experience a drag in performance. This is because the prices of such stocks are completely justified by their fundamentals.

In the presence of investor irrationality, deviations from market efficiency predictions could occur, resulting in divergences of market prices from their fair values. The discrepancy between the fair and market value of stocks is described as "noise". The concept of noise trading was introduced by Siegel (2006) in his noisy market hypothesis. The noisy market hypothesis states that markets are prone and vulnerable to unpredictable temporary shocks that prevent asset prices from always reflecting their true value. These shocks are caused by irrational market participants such as insider traders, institutional investors, momentum traders and speculators who trade in stocks for reasons unrelated to the underlying value of those stocks. Other factors such as behavioural biases, lack of information and different methodologies employed affect investors' estimation of the true value of a share (Mar, Bird, Casavecchia & Yeung, 2009). Shefrin and Statman (1994) assert that, contrary to the values predicted by the EMH, noise traders cause prices to drift away, thereby creating opportunities for arbitrage. The prices of these stocks are unfairly bid up or down and the fundamental factors (risk and growth) that should be reflected in stock prices are distorted and no longer reflective of their fair value.

Just as the EMH does not guarantee the equivalence of stock prices with fundamental values at all times, but that the market portfolio – a cap-weighted index - cannot be outperformed without costly analysis in trying to find mispriced stocks, the noisy market hypothesis does not also characterise each stock price movement as a deviation from the fundamental value of the stock. However, if the deviations do not reflect underlying risk and growth potential of the stocks, some stocks become overvalued while others are undervalued. It therefore becomes costly, if not difficult, to capture individual stock mispricing by analysing individual stocks but constructing a broad

based index, weighted by a non-price-related attribute, can be more mean-variance efficient compared to the market portfolio.

In the presence of investor overreaction and subsequent mispricing of stocks, a cap-weighted model over-weights overvalued stocks and the simultaneous under-weights undervalued stocks (Arnott, Hsu & Moore, 2005). Asness (2006) and Blitz and Swinkels (2008), argue that if cap weighting condemns overvalued stocks to being over-weighted and undervalued stocks to being under-weighted, then a non-cap-weighting methodology, such as fundamental indexation, does the exact opposite.

The noisy market hypothesis serves to provide a plausible explanation for the observed excess returns generated by value and small size stocks as well as the superior performance of the newly introduced fundamental indexation. The rationale of noisy market hypothesis had been, much earlier, implied by Shiller (1981) and LeRoy and Porter (1981), who found that share price movements are way too volatile to be justified by subsequent changes in dividends. Perold (2007) nonetheless criticises the logic of the noisy market hypothesis because proponents of fundamental indexation assume a fair value in the information set when estimating the theoretical expected return of cap-weighted portfolios. This is a violation of one of its own very foundations that fair values are unobservable.

2.8.2   Fundamental Indexation

Fundamental indexation is a weighting methodology applied in the construction of indices whereby stocks are weighted according to the values of their fundamental variables – such as, sales, dividends, earnings, cash flows, et cetera - as opposed to their market prices. Fundamental indexation was first introduced by Arnott et al. (2005) in their groundbreaking research on U.S. stocks where they employed the values of price-insensitive fundamental metrics of size as the weighting parameter for constructing indices. The results reveal that weighting stocks on the basis of fundamental variables such as book value of equity, sales, dividends, cash flow, et cetera, generated statistically significant excess risk–adjusted returns, with lower volatility but higher resilience, relative to their cap-weighted counterparts.

The methodology is based on the independence assumption that price-insensitive metrics of size (fundamental variables) are immune to noise/shocks inherent in market prices. Fundamental weights, therefore, are an unbiased estimate of unobservable fair value weights and any errors in the value of fundamental variables are statistically independent of, or uncorrelated with, market values (Hsu, 2006). Kaplan (2008) pillories the independence assumption by mathematically decomposing the fair value of a stock into its fundamental measure of size and a fair value multiple and his investigation corroborates the critique of Perold (2007) that the independence assumption of the error term, the fair value multiple and the fundamental measure of size is based on logic and math that is internally inconsistent.

The critique of Kaplan (2008) is out of tone with the work of Hsu (2006), who demonstrates how erroneous weighting of mispriced stocks using cap-weighting methodology results in the underperformance of cap-weighted portfolios and that the expected return of fundamental indices is higher than that of market-weighted indices. Hsu (2006) describes this underperformance as a return drag in cap-weighted portfolios and that the return drag in cap-weighted portfolios is the square of the noise inherent in stocks. Perold (2007) retorts that the alleged erroneous under-weighting and over-weighting of stocks under the cap-weighted methodology does not necessarily create a return drag. Treynor (2005) demonstrates that at any defined level of investment, cap-weighted investors own less than the true value of their shares relative to an alternative non-cap-weighted investor. Arnott, Hsu and West (2008) state that, by delinking price from the portfolio weight, the fundamental indexing methodology bypasses bubbles, thereby providing a powerful alternative to investors disappointed by the hollow promise of active management, as well as disenchanted by the traditional cap-weighted index funds.

2.8.3   Advantages of Fundamental Indexation

A.   Avoidance of Return Drag

The noisy market hypothesis, by Siegel (2006), suggests that speculative traders, who trade in stocks for reasons unrelated to the price, cause stock values to deviate from their equilibrium prices. Black (1986) also highlighted the fact that inefficiencies in

stock markets are bound to exist in the presence of noise trading. Treynor (2005) and Hsu (2006) show that when these stocks are cap-weighted, it results in a return drag in performance. By utilising price-insensitive metrics of size in weighting stocks, the return drag inherent in cap-weighted portfolios is mitigated.

The logic in return drag is built on both the over-weighting of overvalued stocks by cap-weighted portfolios and the subsequent reversal of the mispriced assets. When prices of overpriced stocks (that have been over-weighted in the cap-weighted portfolio than is justified by their fundamental values) mean revert, the overpriced stocks generate lower returns. Fundamental indexation only increases the weights of stocks when the values of fundamental variables increase, irrespective of the price movements. Arnott et al. (2005) show that weighting stocks on metrics independent of the price is an intuitive strategy that avoids the return drag and generates higher returns with comparative risk levels.

Despite the return drag of cap-weighted indices, they do have certain advantages, which are also retained by fundamental-weighted portfolios but not by alternative investment strategies such as value investing.
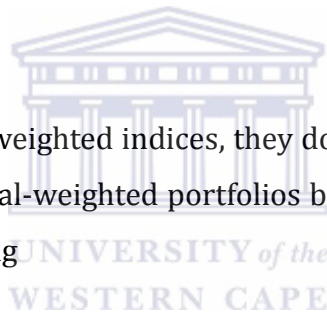
B. High liquidity and Investment Capacity

Cap-weighted portfolios, by design, tend to invest in stocks with large market capitalisation and liquidity. This allows investors to channel their funds into the largest companies in the market. Arnott et al. (2005) state that, fundamental attributes of size (such as; sales and book value) are also highly correlated with market capitalisation and liquidity. This implies that stocks with large market capitalisation tend to have large values for these fundamental variables. Therefore applying fundamental indexation does not deprive its practitioners from partaking in the benefits of large investment capacity and liquidity, which in turn mitigate transaction costs. Arnott et al. (2005) show that fundamental-indexed portfolios exhibit even higher liquidity than cap-weighted portfolios due to the lower concentration ratios of fundamental indices.

C.   Broad Equity Market Representation

Cap-weighted indices allow investors to participate in the broad equity market because the cap-weighted portfolio is assumed to be representative of all the assets in the market. Fundamental indexation, as opposed to other known investment styles, also allows investors to get a slice of all the stocks represented on the broad equity market; only the proportions invested in the stocks differ. Critics of fundamental indexation such as Blitz and Swinkels (2008), allege that if cap-weighted indices overweight overvalued stocks, then fundamental indices inevitably overweight undervalued stocks. The differing weights, however, do not preclude investors under both index methodologies from benefitting from broad equity market representation.

2.8.4   Fundamental Indexation: Active or Passive Strategy?

In light of the fact that fundamental indexation requires portfolio weights to reflect their fundamental values, it is imperative that stocks be rebalanced at predefined logical intervals to mitigate the event of stock weights being out of sync with their fundamental weights. This has been one of the debatable subjects of the superiority of this methodology and the dilemma of whether it is an active or passive strategy. Fundamental indexation has been described by Asness (2006) as a value (active) strategy in disguise, owing mainly to the portfolio rebalancing required. Under cap weighting, portfolio rebalancing is done automatically, dispensing with any resulting transaction cost and as such is considered a passive investment strategy. Fundamental indices are considered passive in terms of the mechanical or rules based nature employed by the methodology but active in terms of the subjectivity inherent in the objective timing decision, which could dramatically alter the return distribution in any given year (Blitz, Grient & Vliet, 2010). Blitz, Grient and Vliet (2010) provide evidence to support the argument that the rebalancing date of the fundamental indices has statistically significant return variation patterns. This indicates that fundamental indexation involves active management to a greater or lesser extent but the active management costs do not erase the excess returns generated by the methodology. Fundamental indexation also benefits from broad equity market participation, whereas value investing does not.

2.9   Conclusion

This chapter discusses the various asset-pricing models, based on the different assumptions about the efficiency of markets. The merits and foibles of the different models are discussed and the most appropriate model, under specified market conditions, proposed. EMH and the law of one price form the foundation of MPT, and expected utility (EU) theory advocates for models that rely on investor rationality and assume a linear relationship between expected return and risk of an asset, such as the CAPM.

However, observed weaknesses of the CAPM due to the tenuous and generous assumptions on which it rests have led to the introduction of other asset pricing models. Moreover, the rationality of investors in the market and the efficiency of the markets have been challenged by behavioural financiers. Kahneman and Tversky (1979) introduce prospects theory to illustrate how human emotions and heuristics can dissuade investors from acting rationally.

The chapter concludes with the discussion of the noisy market hypothesis and overview of the theoretical work underpinning fundamental indexation. Despite being heavily criticised, advocates of fundamental indexation advance sound reason to justify the observed superiority of the concept. The differences and advantages of fundamental indexation over value investing are also discussed.

In conclusion, asset pricing can be described as a spectrum, with the most appropriate model for the pricing of assets chosen to be congruent with the caprice of the market and vagaries of investor behaviour inherent in the market where the pricing occurs. Should markets be deemed efficient and investor behaviour rational, EU theory lays down the parameters for asset price modeling. However, when markets are inefficient and investor behaviour irrational, behavioural finance (prospects theory) and noisy market hypothesis dictate the more appropriate asset pricing mechanisms.

Chapter 3 : REVIEW OF PRIOR LITERATURE

3.1   Introduction

The EMH and the models it underpins have attempted to predict the prices of assets based on rather unrealistic assumptions about equity markets and investor behaviour. Poignant deviations from the assumptions of EMH have been observed, with the efficiency of markets brought under intense scrutiny. Despite profound attempts to justify the mean-variance-efficient status of the capitalisation-weighted market portfolio, anomalies have been consistently observed, with other investment and stock weighting methodologies employed that generate alphas over and above the market risk-adjusted return. While some of these strategies (such as value, size, and momentum investing) have been based on stock selection techniques, other techniques have employed weighting methodologies based on price-insensitive metrics of size.

Fundamental indexation (FI) is an indexing technique, which weights stocks for inclusion in the index on the basis of the value of fundamental measures of size such as sales, dividends, cash flow and book value. This method of indexing has proven to be more mean-variance efficient than the conventional capitalisation weighting methodology employed by most equity market portfolios. Whilst the superior performance of fundamental-weighted indices has been attributed to the noise inherent in stock markets that cause prices to deviate from their fair values and the subsequent erroneous cap weighting of stocks based on misleading prices, other justifications for this observation have been advanced and are underway. This chapter reviews some of the prior literature and empirical findings of research performed around the world on fundamental indexation and the possible reasons put forward for the observed results. Evidence both in support of, and against, fundamental indexation is conjunctively discussed in this chapter, as well as considerations of alternative approaches to stock weighting.

3.2   Evidence from the U.S. Market

Prior to the year 2005, there had been numerous research aimed at exposing the suboptimal nature of the market, and investment techniques such as value investing (Basu, 1975) and size effect (Banz, 1981) were employed to seize the opportunities afforded by the inefficiency inherent in equity markets as a result of market noise precipitated by irrational behaviour.. However, Arnott, Hsu and Moore (2005) were the first to introduce the concept of fundamental indexation and performed research on the U.S. equity market over the period 1962 to 2004 to investigate the relative performance of their innovative fundamental indices and the conventional cap-weighted index. By re-ranking the stocks of the cap-weighted Russel 1000 index by predefined fundamental metrics of size (sales, cash flow, dividends and book value), Arnott et al. (2005) form individual fundamental indices and a fundamental composite index composed of the average of the four fundamental indices. In order to mitigate cyclical effects in the value of the fundamental measures, a trailing five-year moving average is computed for all fundamental indices, with the exception of book value. Arnott et al. (2005) also construct a cap-weighted reference portfolio, using the same methodology employed in constructing the fundamental indices but using cap weights. The S&P 500 is used as the market proxy. As a result of intermittent deviations of fundamental weights from beginning of year weights due to movements in fundamental metrics values and changes in prices, rebalancing of the fundamental portfolios is done on the last trading day of each year. Upon evaluation of the empirical results, the fundamental indices, on average, outperform the market proxy and reference portfolio by 1.97% and 2.15% respectively, with comparative or lower risk, measured in terms of volatility and beta. The dividends index reveals significantly lower values for volatility and CAPM beta while the sales index is the best performing fundamental index overall, outperforming the reference portfolio by 2.56%.

The lower CAPM beta and volatility of the dividends index is illustrative of the fact that dividend-paying companies are relatively stable and more mature compared to non-dividend paying companies. Dividend-paying companies also have deemphasised growth potential and therefore lower market beta risk. Despite the comparative return relative to other fundamental indices and lower risk inherent in the dividends index, Stotz, Wanzenried and Döhnert (2010) criticise the plausibility of the dividends index

used by Arnott et al. (2005), stating that, because some companies prefer not to pay dividends and would rather reinvest their earnings in the buying back of shares, the dividend metrics might result in an index composition that is geared towards mature companies. Arnott et al. (2005) attempt to overcome the problem of non-dividend-paying companies by assigning a zero value to such companies and only using the average of the available fundamental metrics in constructing the fundamental composite index. The dividend bias mitigating effort of Arnott et al. (2005) only illuminates the problem highlighted by Stotz et al. (2010), who propose a more salient solution to the problem by constructing an index of non-paying dividend stocks, with equal weights assigned to each of the stocks.

Still on the discussion of dividend performance, if Shiller's (1981) stipulation of the variation of stock market prices being way too volatile than can be justified by dividend movements is valid, then a fundamental indexation strategy that focuses on investing in stocks with high dividend values or high dividend yield ratios should generate much higher returns. Campbell and Shiller (1988) conduct a study, from 1926 to 2001, to investigate the ability of dividend yields in predicting stock returns. They measure the dividend yield of S&P 500 stocks for each quarter and calculate their subsequent ten-year return over the entire period. Based on the initial level of the dividend yield, they divide the observations into deciles. They observe that stocks that were purchased with initial dividend yields that were relatively high earned relatively higher stock market returns and vice versa. They also find that dividend yield predicts as much as 40 percent of aggregate market share price movements.

While this finding provides further support to the potency of high dividend values relative to market price in generating superior returns, Malkiel (2003) argues that the higher returns generated by the stocks with higher dividend yield may just have been as a result of stock market adjustments to general economic conditions. Malkiel (2003) further stipulates that, because dividend yields tend to fluctuate in line with interest rates, fundamental metrics of size (such as dividend) might not be any particularly better reflection of the fair value of stocks.

Post the mid-1980s, dividend yields for companies have dropped significantly and should this drop be interpreted in the light of stock returns, an expected low equity market return should be predicted from investment in stocks with relatively high dividend yield. Fama and French (2001) construe the observed drop in dividend yield as a change in the dividend behaviour of U.S. corporations in terms of their willingness to exercise stock repurchase, as opposed to increased dividend payout; an argument parallel to that provided by Stotz et al. (2010). Fluck, Malkiel and Quandt (1997) argue that a dividend-based investment will not outperform consistently, especially when applied to individual stocks. Making reference to the "Dogs of the Dow Strategy", whereby the top ten stocks, based on dividend yields, of the Dow Jones Industrial Average (DJIA) were invested in, Fluck, Malkiel and Quandt (1997) call attention to the fact that the investment yielded significantly higher returns for the first few periods. However, the investment subsequently underperformed the market average return when "Dogs of the Dow" mutual funds were introduced to the market and eccentrically sold to investors during the 1995-1999 period. The results of Arnott et al. (2005) nonetheless portray a continuous outperformance of the dividends index post the 1999 period, contrary to the arguments forwarded by Fluck et al. (1997).

Assuming a 2% round-trip transaction cost for the fundamental indices, Arnott et al. (2005) demonstrate that the average alpha of fundamental indices only drops from 2.15% to 2.01%. With turnover values of 6.3%, 13.1% and 10.6% for the reference portfolio, fundamental indices and fundamental composite index respectively, a one-way transaction cost and round trip transaction cost in excess of 16% and 24.9% respectively is required to completely erode the alpha of the fundamental composite index, which displays a much lower turnover relative to the individual fundamental indices.

In addition to both the basic return and risk-adjusted return outperformance of fundamental indices over cap-weighed indices, Arnott et al. (2005) find that fundamental indices are more resilient during bear markets and in periods of falling interest rates, outperforming the cap-weighted portfolio during such periods. Despite the growth bias of cap-weighted indices during bull markets, fundamental indices still match the cap-weighted index's performance.

Post the calculation of liquidity and concentration ratios for fundamental indices, evidence of the retention of some of the benefits of capitalisation weighting by fundamental indexation is also highlighted. Liquidity ratio, which measures the investment capacity of the fundamental indices, indicates that on average fundamental indices retain about 50 percent of the investment capacity of cap-weighted indices, with the employment index and the dividends index yielding the lowest and highest ratios respectively. Similar findings are observed with the concentration ratio. Although the ratios may not seem large in absolute value terms, relative to an equally weighted methodology, the ratios are comparatively higher.

In all the overwhelming results displayed by the empirical work of Arnott et al. (2005) through their novel investment strategy, a substantial amount of criticism has been advanced, questioning both the logic of their portfolio construction model and the rationale underlying the observed performance. The critiques extend beyond the original fundamental indexation paper to that of other proponents of fundamental indexation and will be discussed intermittently.

To begin with, Bogle and Malkiel (2006) insinuate that the concept falls short of being revolutionary and is simply a repackaging of value investing. Asness (2006) describes fundamental indexation as value investing in disguise, while Skaanes (2007) says the concept is like old wine in new wineskin.

Moreover, Amenc, Goltz and Ye (2012) present flaws in the anatomy of fundamental index portfolios by making informed comparisons between the heuristic-based-weighting methodologies and optimisation-based-weighting methodologies, whereby alternative weighting schemes are heuristic-based while the capitalisation weighting schemes are optimisation-based. Amenc et al. (2012) stipulate that portfolio constitution affects the performance of both methodologies differently. Tu and Zhou (2011) showed that heuristics-based approaches work best in larger stock universes while optimisation-based approaches work best in smaller stock universes. In the light of the differences in portfolio constitution affecting performance, Amenc et al. (2012) make reference to the difference in portfolio constitution of the fundamental indices and market proxy used by Arnott et al. (2005). Amenc et al. (2012) state that, making

performance comparisons between the S&P 500, which only has 500 constituents and the fundamental indices constituting 1000 stocks is not logical because the larger universe of fundamental indices introduces a small-cap exposure and, moreover, "like should be compared with like". This argument is however tenuous since Arnott et al. (2005) also construct a reference cap-weighted portfolio using both the same methodology and constituents as the fundamental indices. The reference portfolio, as well, is effectively outperformed by the fundamental indices.

What is more, Amenc et al. (2012) assert that fundamental indexation is a stock selection model, which does not necessarily pick the same stocks as the cap-weighted portfolio. Hsu and Campollo (2006) rightly note that fundamental indexation only includes stocks that grow their fundamental attributes alongside their market capitalisation, which may not necessarily coincide with the stocks selected by a cap-weighted index. Stock selection is likely to create certain stock-selection-related biases, thereby generating added value that needs to be accounted for when making useful comparisons with a model that does not employ stock selection. The performance analysis of Arnott et al. (2005) fails to account for the other style anomalies inherent in stock selection. In fact, justification for the results of the empirical work of the founders of fundamental indexation has not been provided with any level of adequacy in their paper. They, however, suggest possible reasons for the superior and robust performance of fundamental indices being; superior portfolio construction, market inefficiency, hidden/additional exposure to distress risks or a combination of the aforementioned reasons.

The most salient rationales for the outperformance of fundamental indices over cap-weighted indices have been provided by other authors such as Hsu (2005), Treynor (2005), Siegel (2006), Hsu and Campollo (2006) and other subsequent researchers as discussed below.

Chen, Chen and Bassett (2007) pave the way into new approaches for determining the "intrinsic value" of stocks using non-conventional methods of estimating fundamental values (as opposed to the one employed by Arnott et al. (2005). Their approach is two-fold: Firstly, they estimate fundamental values based on the assumption that stock

prices are comprised of a fundamental value and deviations from the fundamental value. Secondly, on the assumption that stock prices are noisy, as predicted by Siegel (2006: 2007), they smooth the weights of market stock prices in an attempt to mitigate the noise.

Under the first fold of their approach, they derive weights based on three alternative specifications being; i) that the fundamental price is constant, ii) the fundamental price is constant plus a noise (deviation), iii) the fundamental price is a random walk. Under each of the specifications, they derive fundamental weights in constructing fundamental portfolios and find that the fundamental-weighted portfolio outperforms the cap-weighted portfolio, with results similar to a fundamental-weighted portfolio constructed with pre-defined values (constant price).

The second fold of their approach is more extensive. Using the data from CRSP, they obtain stock price data for the top 1000 stocks by market capitalisation. Their sample period runs from January 1962 to December 2003. Cap-weighted portfolios are constructed in the conventional fashion but the fundamental values for fundamental-weighted portfolios are found by obtaining the median value of the stock's cap weight within a fixed window period over the immediate past. The immediate past is described as the 12*n previous months from the month in question. Where, "n" refers to the number of previous years chosen as the window period. The median cap-weights are called smoothed cap weights. The median, as opposed to the mean, is implemented for robustness purposes. Portfolio rebalancing is adjusted after 12 months but in order to account for January effect, two rebalancing dates are used: January and June. Adjustments to fundamental weights are effected in order to factor-in events such as; mergers, spin offs and acquisitions. A general observation of the results indicate that, all fundamental-weighted portfolios using the smoothed cap weights outperform the cap-weighted portfolios, irrespective of the rebalancing date, by an average of 1.0% per annum, with lower volatility. The performance of portfolios rebalanced in January and June are akin and performance improves with longer estimation windows.

Although these results portray the superiority of fundamental indexation, despite a rather novel approach for estimating fundamental weights, the absence of accounting

for additional cost inherent in the methodology does not lend robustness to the results; especially with the meager 1.0% gap in performance. The application of the median, as opposed to the mean, can be misleading and generate results similar to that of a purely cap-weighted index, if price noises are protracted and exhibit a high degree of cross-sectional correlation. However, because fundamental indexation feeds on the deviation of stock prices from their fundamental values and the subsequent reversion of prices to their intrinsic values, the application of the median is still appropriate.

Still on the U.S. market, Hsu and Campollo (2006) replicate the studies of Arnott et al. (2005), and Tamura and Shimizu (2005) using 20 years of data stretching through the period 1984 to 2004. They construct 23 fundamental indices and compare the value added by the fundamental indices relative to the MSCI cap-weighted index. Fundamental indices for both the U.S. (RAFI U.S.) and the world (excluding the U.S. – RAFI World) are constructed and comparative cap-weighted MSCI U.S. and MSCI world indices are also used as performance benchmarks. On average return basis, the RAFI U.S. outperforms the U.S. MSCI cap-weighted index by 2.8% while the RAFI World outperforms the MSCI World by 3.5%. Hsu and Campollo (2006) attribute the outperformance of RAFIs to superior portfolio construction as opposed to stock selection; a finding that is well in opposition to that of other European and world studies (Stotz et al., 2010; Mar, Bird, Casavecchia & Yeung, 2009) where the outperformance was found to be steered by exposure to unique investment styles and factor risks premiums. Like Hsu (2005) and Treynor (2005), Hsu and Campollo (2006) also observe that the maverick risk (return drag) in cap-weighted portfolios is linked to the level of the price noises and that the return drag is pronounced when mispricing is temporary.

What is more, Hsu and campollo (2006) highlight the fact that despite frequent association of the performance of fundamental indices to value effect, fundamental indices are far from simple value investing, as they retain most of the benefits of cap-weighting, which value investing does not, and fundamental indices also incur lower turnover costs. Hsu and Campollo (2006) also predict scenarios and economic environments in which fundamental indexation is more likely to outperform capitalisation weighting. During periods of rapid and irrational P/E expansion, fundamental indices will take an upper hand in performance due to their rebalancing

away from stocks with large market capitalisation relative to the value of their fundamental attributes.

One favourable attribute of any objective benchmark index should be its ability to mitigate large dispersions in its performance, resulting from timing of reweighting or rebalancing of its constituent stocks. Most of the studies on fundamental indexation have typically chosen one rebalancing date for all its fundamental indices. Blitz, Grient and Vliet (2010) uncover the fact that the choice of rebalancing dates for a fundamental index produces more than just a nuance in the performance of the index. Over the period January 1991 to December 2009, Blitz et al. (2010) compare indices consisting of the 1000 largest U.S. stocks apropos fundamental values and market capitalisation. The fundamental variables used are sales, cash flow, dividends and book value. Using trailing five-year average values for all fundamental variables, except book value, Blitz et al. (2010) construct fundamental indices, each rebalanced at the end of a different quarter of the year (March, June, September and December). They also construct a fundamental composite (alternative) index, comprised of equal proportions of the four fundamental variables, which is rebalanced by only one-fourth every quarter, depending on the fundamental variable predefined to be rebalanced at the quarter in question.

The results indicate that although fundamental indices, on average, outperform the cap-weighted index, as observed in the Arnott et al. (2005) study, fundamental indices, with different rebalancing dates, outperform the cap-weighted index by different magnitudes over the years. For instance, the fundamental indices with annual rebalancing at the end of December, March and September outperform the cap-weighted index by an estimated two percentage points (2%) while the June-rebalanced index does so by only 1.4%. In 2009, the RAFI 1000 rebalanced in March outperforms the Russel 1000 index by 13.6% while the September RAFI 1000 underperforms the Russel 1000. The results of this study are confirmed by the cross-tracking errors of the fundamental indices. Albeit the fundamental indices display a tracking error of about 5% against the cap-weighted portfolios, their cross tracking errors vary by as much as 1.4% to 2.1%, similar to that observed in low-risk, active management strategies.

Blitz et al. (2010) attribute the differences in performance for the fundamental indices with different rebalancing dates to:

1) Dissimilar value exposures, which dramatically change the sensitivity of fundamental index returns to the subjectively chosen rebalancing date.

2) Relatively large cross-tracking errors.

Despite the performance differences observed in March 2009 - being more or less attributable to luck as opposed to investment skill - such large differences in performances of indices due merely to the choice of rebalancing dates is not appropriate for a broad market index. Blitz et al. (2010) use the Augmented Dickey-Fuller test to prove that large deviations in stock weights of fundamental indices do not show subsequent mean-reversion. To overcome the problem, they propose the use of the blended (alternative) fundamental index.

Evidence of the superior performance of fundamental indexation within the U.S. market has been extensive and substantial. In addition to fundamental indexation being dominant over cap-weighted indexing, in terms of risk-adjusted returns (in equity markets), Arnott, Hsu, Li, and Shepherd (2010) reveal the outperformance of fundamental indexation in fixed income markets. They found that the fundamental index strategy outperforms their cap-weighted counterpart by 260 basis points (2.60%) annually in the U.S.-high yield corporate debt market and by 40 basis points (0.4%) annually in the U.S.-investment grade corporate debt market. Similar results are observed by Shepherd (2011), who based his research on the RAFI U.S. Corporate Fundamental Bond Index series. Fundamental indexation on fixed income securities, however, is beyond the scope of this research, which focuses on equity markets but the outperformance of fundamental indexation in both markets has been triggered, in large, by the same underlying reason; the noise-in-price hypothesis, that creates the return drag in cap-weighted portfolios and the subsequent reversion of mispriced stocks to their mean value.

3.3   Evidence from the European Market

On the European market, fundamental indexation has also been tested with a fairly consistent observation in the performance of fundamental indices relative to cap-weighted indices. Hemminki and Puttonen (2008) construct fundamental indices and a reference portfolio by re-ranking and reweighting the stocks of the Dow Jones Euro Stoxx 50 index over the period January 1996 to December 2006. The DJ Euro Stoxx 50 index, derived from the DJ Euro Stoxx Total Market Index, comprises of 50 stocks that provide a blue-chip representation of supersector leaders in the Eurozone, made up of 12 Eurozone countries. The DJ Euro Stoxx 50 index represents about 60 percent of the free float market capitalisation of the DJ Stoxx Total Market index, which on its part represents approximately 95 percent of the free float market capitalisation of the 12 Eurozone counties included in the index construction. The data source is the DJ World index, which is a global stock index comprising of about 6,500 stocks that represent about 95 percent of the worldwide free float market capitalisation. The 12 countries constituting the index are: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain. The index is therefore sufficiently representative of the market.
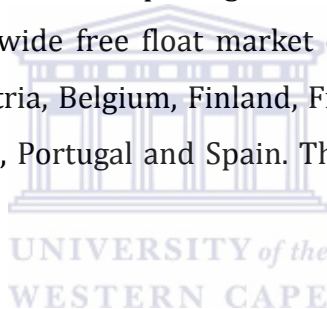
The fundamental indices constructed are dividends, sales, cash flow, total employment, book value of equity and the fundamental composite index. Year-end values for the fundamental attributes are obtained and the indices rebalanced on the last day of the calendar year and retained for the following year. A reference portfolio, weighted by market capitalisation is also constructed according to the methodology employed in constructing the fundamental indices. Constituent weights in each portfolio are capped at 10 percent of the free float market capitalisation or aggregate fundamental value.

Because the number of constituent stocks and weighting criteria is similar for the DJ Euro Stoxx 50 index and reference portfolio, these two indices would be expected to be alike in terms of both their constituent weights and performance. However, they are not, because while the DJ Euro Stoxx 50 index is rebalanced in September, the reference portfolio is rebalanced in December. The three-month-lag introduces differences due to intermittent changes in stocks market capitalisation.

As opposed to the trailing five-year average values employed by Arnott et al. (2005), Hemminki and Puttonen (2008) use the trailing three-year average values of the fundamental metrics of size and the fundamental composite index is formed by combining all five fundamental attributes in equal proportions. Arnott et al. (2005) did notice that the use of different trailing average number of years does not reveal results that are significantly different.

Hemminki and Puttonen (2008) observe that, on average, the fundamental indices generate an alpha of 1.76%, with higher risk-adjusted returns relative to the cap-weighted market index (reference portfolio). However, only the book value index, dividends index and fundamental composite index generate statistically significant returns in excess of the reference portfolio while the sales index, dividends index and the fundamental composite index display lower volatility than the cap-weighted reference portfolio. The cap-weighted reference portfolio, on its part, outperformed the market proxy (DJ Euro Stoxx index) in terms of arithmetic and geometric returns but with slightly higher standard deviation.

The results of the Hemminki and Puttonen (2008) study are somewhat similar to the findings of Arnott et al. (2005) in terms of the average outperformance of the cap-weighted reference portfolio by the fundamental indices. With regards to individual performance by the fundamental indices, there are conspicuous variations. The sales index, which was the best performing index in the original study, only displays a rather average performance in this study. The dividends index is the best performing fundamental index in terms of geometric returns and risk-adjusted returns and retains the property of having lower volatility relative to all other portfolios – with reasons for lower risk measures already suggested in the Arnott et al. (2005) study above. Hemminki and Puttonen (2008) recommend the use of the book value index or dividends index for investing in equity markets.

Because the portfolios are relatively highly concentrated; that is, only 50 stocks chosen from a universe of 6,500 stocks, it can be expected that the performance of fundamental indices would have been much better had portfolio concentrated been reduced. This is in line with the results of a study by Hsieh, Hodnett and Rensburg (2012), in which they

investigate the effect of portfolio concentration on both fundamental weighted and cap-weighted portfolios. Hsieh et al. (2012) find that in addition to fundamental indices outperforming cap-weighted indices throughout the examination period, cap-weighted indices are susceptible to a return drag when portfolio concentration is lowered (That is, from 50 through 100 to 200 stocks).

Irrespective of the favourable results observed from the application of price-insensitive attributes in the weighting of stock indices, the empirical work of Hemminki and Puttonen (2008) can be criticised on several fronts. Firstly, the 10-year research period, though representative of both bull and bear markets, is relatively short compared to other studies (Arnott et al., 2005). A longer research period would have been more representative of economic conditions and how the different weighting schemes performed therein. Secondly, the study does not account for transaction cost and turnover. The rebalancing assumption associated with fundamental indexation has been found to generate transaction cost over and above the reconstruction costs incurred by cap-weighted portfolios. Accounting for turnover should reflect more plausible results. This research assumes equality of transaction costs and management fees for the cap-weighted and fundamental weighted portfolios. The high level of concentration of the portfolios might, nonetheless, be reason for substantial reduction of the turnover for fundamental indexation. Thirdly, like the Arnott et al. (2005) study, this study fails to account for investment style risks and priced risk premia such as size, value and momentum.

Despite the traction gained by fundamental indexation and the charted dominance of the strategy over cap-weighted indices, Stotz et al. (2010) criticise the work of some of their predecessors. They illuminate the fact the Jensen's alphas calculated is based on the CAPM benchmark, which is a single factor model and ignores some other style risk premia such as value and size introduced by Fama and French (1993) and the additional momentum factor in the four-factor model introduced by Carhart (1997). Stotz et al. (2010) therefore perform a more extensive risk analysis, incorporating value, size and momentum in their risk-adjusted return workings, as well as introducing the concept of accounting data risk, described as the differential risk inherent in the economic attributes of different companies. Stotz et al. (2010) posit that investors assign different

valuations to the fundamental variables of different companies based on their volatility assessment of the fundamentals. Under the assumption that investors have a quadratic utility function, they show how investors derive a certainty equivalent of the risky fundamental metric, assigning lower weights to companies/stocks with perceived riskier fundamental metrics.

Stotz et al. (2010) also apply index weight ratios to gauge into what primarily drives the performance of fundamental indexation. The index weight ratio is the quotient between the stock's fundamental-to-price ratio and the market's fundamental-to-price ratio. Finally their research extends the examination period of their European predecessors by four years, stretching from July 1993 to April 2007.

Using the DJ Stoxx 600 index, Stotz et al. (2010) construct fundamental indices for sales, cash flow, book value and dividends. They also construct an equally weighted index for non-dividend paying companies. In line with the technique of Arnott et al. (2005), a cap-weighted index and fundamental composite index is also constructed. The results indicate that fundamental indices, on average, outperform their cap-weighted peers by 1.7% per annum. Albeit all fundamental indices outperform the cap-weighted index, with similar measures for volatility, cash flow is the best performing fundamental index in terms of mean return but the dividends index generates lower volatility for same reasons discussed earlier. The equally weighted index of nonpaying dividend stocks underperforms the cap-weighted index and displays higher volatility. In an earlier work, Lakonishok, Shleifer & Vishny (1994) attribute the underperformance of nonpaying dividend indices to the predominant constitution of growth stocks in this index and the propensity of them being overvalued by irrational investors.

Based on risk analysis using the Fama-French (1993) three-factor model, Stotz et al. (2010) find that fundamental indices display a positive exposure to the value factor but a negative exposure to the size factor; the two effects about cancel out each other, thereby producing almost similar values for the Jensen's alpha and Fama and French's alpha. In relation to the Carhart (1997) four-factor model, alphas generated are slightly lower than that from the Fama-French (1993) three-factor model but with similar levels of significance. Almost all fundamental indices reveal a negative coefficient for the

momentum factor, which aims to capture the contrarian characteristics of the fundamental indices.

Lastly, the stock's fundamental-to-price ratio is found to be the primary driver of the returns of the fundamental indices and also to have predictive power for the cross-section of stock returns and power to forecast the time series of market returns. Stotz et al. (2010) conclude that even though value has explanatory power for the returns of fundamental indices, the fundamental weights are a better reflection of the true value of the company's worth than market values, which tend to be smeared by unrealistic and irrational estimates of the growth prospects of a company. Stotz et al. (2010) also recommended the use of the fundamental composite index, which mitigates the possible flaws of any single individual fundamental index.

3.4 Evidence from the Australian Market

Contrary to the above evidence of fundamental indexation outperforming cap-weighted indices on a return and risk-adjusted return basis, evidence from the Australian market seems to uncover more extreme findings. An examination into not only the relative performance of fundamental indexation and cap-weighted indices but also the underlying cause of observed results is performed by Mar, Bird, Casavecchia & Yeung (2009) over the period 1995 to 2006. After selecting and ranking the top 200 stocks by size, measured in terms of economic variables and market capitalisation, the stocks are weighted and portfolios of both fundamental indices and capitalisation weighting formed. In tandem with previous research, a fundamental composite index is also constructed but the sales and the dividends indices, which were included in previous research, are not part of this research. Instead, revenue is introduced.

The results of the research indicate that fundamental indices, on average, outperform the cap-weighted index by 1.94%, with slightly greater volatilities. Similar to Stotz et al. (2010), cash flow is the best performing fundamental index with a mean return of 14.53%. Fundamental indices equally outperform the cap-weighted portfolio on a risk-adjusted basis, with a higher Sharpe ratio and Treynor measure, as well as Jensen's alpha. Moreover, fundamental indices outperform the cap-weighted portfolio in all years

except during the tech bubble years (1997; 1998). What is most intriguing about this research is the residual alpha obtained upon regressing the results against the Fama-French (1993) three-factor model and Carhart (1997) four-factor model. The results depict that even though the Carhart (1997) four-factor model is a better model for explaining the performance of fundamental indices (producing higher R-squared values), the value factor proves to be significant across all the models. After controlling for the four factors of the Carhart (1997) model, the residual alpha is not significant. This is in contrast to other findings that relate the outperformance of fundamental indices to noises in stock prices, as opposed to stock selection bias.

Because the universe of stocks employed in the above test might not have been the same, as was indicated by the differing [5]CAP ratios for the fundamental indices and cap-weighted index, it would be difficult to determine if the outperformance of the composite fundamental index is as a result of superior stock selection or superior weighting. In a concomitant test to illustrate the reason driving performance, Mar et al. (2009) limit their relative portfolio constructions to a set of same stocks. Because the 200 stocks are the same, and only the weightings allocated to them by the weighting mechanisms are different, it is found that fundamental indices again outperform cap-weighted indices. This is in support of the advocates of fundamental indexation (Arnott et al., 2005; Treynor, 2005; Hsu, 2006) that fundamental indexation limits the noise in stock weighting due to their price-insensitivity and is, therefore, a better weighting, as opposed to stock selection, technique.

To reconcile the above findings, Mar et al. (2009) conclude that fundamental indices, albeit a better weighting technique, do exhibit characteristics of value portfolios, which predominantly justify the generated alphas. They further state that the value bias also causes fundamental indices to perform poorly during periods of extreme market irrationality.

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[5]As defined by Mar et al. (2009), the CAP ratio determines the investment capacity of the fundamental indices and provides a relative measure of fundamental indices. The ratio is found by dividing the fundamental-weighted average capitalisation of the fundamental index by the cap-weighted average capitalisation.

Blitz and Swinkels (2008) also argue that fundamental indices are nothing but a new breed of value investing. They reveal that when the RAFI 1000 and Russell 1000 indices are regressed against the Fama-French (1993) three-factor model, the alphas drop from 0.19% per month to an insignificant -0.02% per month and from 0.26% per month to 0.10% per month for the RAFI 1000 and Russell 1000 respectively. In addition to being value biased as shown, Blitz and Swinkels (2008) further state that fundamental indexation has even less potential to benefit from the value premium because fundamental indices are designed for simplicity and appeal.

3.5   Evidence from Multi-country Studies

Fundamental indexation on the international market has also received favourable embrace. Early work on fundamental indexation on the international market was performed by Tamura and Shimizu (2005), with their research period running from January 1988 to August 2005. In order to examine the FTSE Developed index, they construct two global fundamental indices (Global FIs); a global fundamental index and a global ex-Japan fundamental index. The Global FIs constitute the 1000 largest fundamental-weighted stocks from 23 countries. They construct a fundamental composite index and a cap-weighted reference index under the same principles employed by Arnott et al. (2005). For benchmarking purposes, they use the MSCI World and the FTSE Developed Indes. Their results indicate that Global FIs outperform the cap-weighted reference and benchmark indices by 3.14% and above 2.0% respectively. In volatility terms, the Global FIs yield volatility levels that are 1% less than other indices. Alphas for all Global FIs are significant in obedience to the findings of Arnott et al. (2005) but mildly inconsistent with Hemminki and Puttonen (2008). In terms of country analysis, all countries also produce positive alphas but with differing magnitudes. Greece and Canada exhibit the highest alphas of 5.65% and 4.32% respectively while New Zealand yields the lowest alpha of 0.13%. One other glaring and bizarre finding with their research was the lower turnover observed in Global FIs, which is rather at odds with Arnott et al. (2005) and most researchers.

Hsu and Campollo (2006) also build on the work of Arnott et al. (2007) and Tamura and Shimizu (2005) to investigate international markets, as well as the U.S. market, as was

discussed earlier. They also find that fundamental indexation prevail over cap-weighted indices in international markets.

In 2008, Lobe and Walkshäusl (2008) expand the research of Tamura and Shimizu (2005) in terms of both the number of countries investigated and the intensity of the test procedure. In terms of country representation, they extend the tally to 50 and, with regards to test intensity, they apply stringent boot-strapping methods to investigate the robustness of the results.

Upon obtaining monthly total return data from the Thomson Financial Datastream and accounting information data for various companies from 50 different developed and emerging markets, Lobe and Walkshäusl (2008) construct global fundamental and cap-weighted indices, and country-specific fundamental and cap-weighted indices, as well as fundamental composite portfolios. Their portfolio construction methodology is consonant with earlier approaches but the number of stocks included in the sample is progressive, as opposed to the restrictions in stock numbers implemented in prior research. The research period stretches across the period July 1982 to June 2008 and portfolio rebalancing occurs annually in June.

At a global level, fundamental indices outperform cap-weighted indices in terms of risk-unadjusted and risk-adjusted returns, with the dividends index displaying the highest terminal value while the book value index is the worst performer of the fundamental indices. Lobe and Walkshäusl (2008) apply the Ledoit and Wolf (2008) bootstrap test for robustness of Sharpe ratios. Post application of the robustness test, fundamental indices still exhibit large significantly positive differences in Sharpe ratios. On a country-specific basis, only 4 (Morocco, Columbia, Venezuela and Taiwan) out of 50 countries investigated generate fundamental-weighted returns lower than their cap-weighted counterparts and half of the countries generate lower fundamental index volatilities. Of the 43 countries that outperformed the cap-weighted portfolio on a risk-adjusted basis, when subjected to the bootstrapping test, only 14 countries persist (11 of 28 developed countries and 3 of 22 emerging markets). This result is largely in controversy with the assertions of Arnott and Shepherd (2009), who found that the emerging market RAFI index adds greater value than the ALSI. Arnott and Shepherd (2009) suggest that

greater mispricing and higher inefficiency in emerging markets facilitate the potential to benefit from the concept of fundamental indexation.

Regression results of Lobe and Walkshäusl (2008) against a single factor model (CAPM) indicate that the monthly alphas generated by all fundamental indices are significant and positive. For country-specific fundamental-weighted portfolios, 14 out of 50 display alphas that are significant at a 5% level of significance.

To test whether or not the performance of fundamental-weighted portfolios are driven by value and small size risk premia, the results, when regressed against the Carhart (1997) four-factor model, indicate that, even though all fundamental-weighted portfolios show exposure to the value factor, with most of them showing exposure to the momentum factor and less than half displaying exposure to the size factor, more than 60% of the fundamental indices still generate significantly positive alphas at a 5% level of significance. This reveals that the proposition by Jun and Malkiel (2008), as well as Blitz and Swinkels (2008) that fundamental indices are nothing more than a value investment strategy in disguise is more than ludicrous. Lobe and Walkshäusl (2008), nonetheless, state that an arbitrarily selected domestic fundamental index is unlikely to outperform its respective cap-weighted index, since only 6 out of 45 country-specific indices achieve an outperformance in their research. Lobe and Walkshäusl (2008) heavily attribute the better performance of the global fundamental-weighted index to their absolute fundamental metric contribution to the world fundamental metric, relative to their market value contribution to the world market portfolio. However, diversification potential, market timing and sector allocation shed little light on the above results.

To investigate the effect of international diversification using fundamental indices, Estrada (2008) constructs global portfolios based on a sample of 16 countries, which constitute over 93% of the world market capitalisation, over the period December 1973 to December 2005. He constructs both cap-weighted and price-insensitive portfolios. The price-insensitive portfolios are both fundamental-weighted and equally weighted. On a fundamental-weighted basis, Estrada (2008) constructs a dividend per share index, which is rebalanced in December. Estrada (2008) also constructs an index built upon the

notion of active investing and generally considered to be a variation of value investing – a dividend yield weighted index (DYWI).

Stock return information is calculated from the Datastream databank and the Datastream World market index is used as the market proxy. By investing $100 in both the dividend per share weighted index (DWI) and the cap-weighted index over the examination period, the DWI generates a higher terminal value than the cap-weighted index, which translates to an annual return of 14.1% and 12.2% respectively. This performance is achieved at only slightly higher risk, measured in terms of volatility: That is, 15.7% for the DWI against 14.3% for the cap-weighted index. The DWI also outperforms the cap-weighted index in 4 of the 6 (non-overlapping) periods in the sample. Although the stocks with large-cap weights such as U.S. and Japan were observed to significantly drop weights in the fundamental-weighted global index (DWI), while all other countries had higher weights in the DWI than in the cap-weighted index, performance was not purely attributed to the assumption that countries with higher dividend yield outperform those with low dividend yield. Upon performing a cross-sectional correlation between dividend yields at two points in time (December 1973 and December 1989) and the subsequent 16-year mean compound returns for the periods 1974-1989 and 1990-2005, as well as the cross-sectional correlation between average dividend yields and mean compound returns, both calculated over the same sample period, results suggest that a greater part of the superior performance is accounted for by the value factor relative to the size factor. This finding is consistent with the conclusion of other researchers (Bernstein, 2006; Schoenfeld, 2006) about the dominance of size and style exposures in the performance of fundamental indices; with a relatively smaller proportion of the excess returns of fundamental indices attributed to the weighting technique.

The greatest contribution of Estrada's (2008) work came from his comparison of the global fundamental-weighted index (DWI) with the performance of the global style weighted index, using a dividend yield-weighted index (DYWI), when $100 was invested in each of the portfolios over the same period. Estrada (2008) realises that, on an international basis, the DYWI outperforms the fundamental-weighted index by an annual 1.7%, at basically same volatility levels and does so with a much fairer

distribution of weights across the 16 countries represented. Even the equally weighted index outperforms the DWI. The results of this research imply that investors in pursuit of global diversification, willing to achieve higher returns, can do so by not only abandoning the traditional buy and hold market portfolio, but the fundamental index strategy as well, in preference of a simple value strategy, at comparable costs.

In 2012, Hsieh et al. (2012) investigate the correlation between the size of a portfolio, constructed in terms of both capitalisation weighting and fundamental weighting, and the return. If the stipulation that the return drag in cap-weighted portfolios is directly proportional to the level of noise in asset prices (Treynor, 2005; Hsu, 2006) and the likelihood of mispricing increase with higher stock price valuations, then the probability of observing misallocation of cap weights in stock prices, as well as trailing performance, is bound to be prominent in stocks with higher market capitalisation.

Applying a similar methodology to that of Arnott et al. (2005), Hsieh et al. (2012) employ the Dow Jones Titan Composite index, within which stocks from 19-second-tier sectors by industry classification are represented. Instead of just constructing one fundamental index for each fundamental variable, as observed in previous studies, they segregate the fundamental indices, as well as the cap-weighted indices, into 4 different categories; the top 200, top 100, top 50 and top 30, capping the weights at 10%: The primary purpose of such segregation being to capture any relative return variations as portfolio concentration changes. Hitherto, most of the research performed on fundamental indexation simply applied the cap-weighting methodology in weighting stocks, but replaced the cap weights with fundamental weights. Whilst fundamental indexation alone cannot be victimised for not applying weight constraints (considering that their comparative cap-weighted portfolios also did not), Amenc et al. (2012) criticised some fundamental indexation advocates for disregarding the weight constraint rules, proposed by Jagannathan and Ma (2003). Jagannathan and Ma (2003) assert that weight constraint rules are applied in portfolio optimisation strategies to minimise concentration and increase robustness of results. The employment of these weight constraints by Hsieh et al. (2012), therefore, alleviates this concern.

The fundamental variables used in constructing the fundamental indices are sales, book value, earnings after tax, dividends and cash flows. The research period, which runs from January 1991 to December 2008 is subdivided into to two periods, representing the bull (1991-1999) and bear (2000-2008) economic phases of the market. The MSCI world index serves as the market proxy and the 3-month U.S. Treasury bill as the proxy for the risk-free rate. The results indicate that all fundamental indices outperform the cap-weighted indices in their respective concentration categories throughout the examination period. Not only do the fundamental indices outperform their respective cap-weighted indices, there are insignificant observable differences in the performance of fundamental index concentration categories as opposed to the inverse relationship between return and portfolio concentration observed in cap-weighted indices. While fundamental indices are more volatile in terms of standard deviation, they display lower than average betas and higher values for risk-adjusted measures relative to cap-weighted indices. Post deduction of transaction costs, fundamental indices still exhibit a higher return.

Fundamental indices earn comparable returns to the MSCI index during the first sub-period but incurred substantially less loss during the second sub-period, meanwhile the cap-weighted indices underperform the market proxy (MSCI index) throughout the examination period. The results of this study have two implications: Firstly, in line with the advocates of fundamental indexation that employing price-insensitive metrics to weight stocks mitigates return drag, the small firm effect (reduction in portfolio performance as portfolio concentration increases) is not present in fundamental-weighted indices. Secondly, fundamental indices are found to be more resilient during periods of market distress. This second implication offers more support to the assertions of Siegel (2006) that fundamental indices afford protection against the impact of speculative bubbles.

Although the research of Hsieh (2013) focused on emerging markets, its employment of the S&P Emerging Large-Mid-Cap index (which in itself is a subset of the S&P Global Broad market index, and includes more than just a few domestic markets) aligns the study to more of an international orientation. However, only the top 300 stocks measured by market capitalisation at the end of each month are extracted for this

research. The study also has many similarities to the previous work of the researcher and his colleagues in 2012 but its objective is to determine what drives the performance of fundamental indices in emerging stock markets – size or value? The research period runs from January 1996 to December 2010 – splitting the period into two sub-periods; with the bull market running from January 1996 to June 2003 and the bear market from July 2003 to December 2010). The monthly-rebalanced cap-weighted portfolio represents the market proxy while the 90-day U.S. Treasury bill represents the risk free. In this study, Hsieh constructs portfolios of different concentrations (100, 50 and 30) using fundamental-weighted and cap-weighted methodology. Equally weighted and fundamental composite indices of similar stock concentrations are also constructed. Fundamental variables enlisted in this research are gross sales, book value, total earnings and total dividends and portfolio rebalancing is done on a monthly basis.

The findings are a tad dissimilar to the work of Hsieh et al. (2012) in that while portfolio concentration did not significantly influence the performance of fundamental indices in the previous research, this research indicates that portfolio concentration has a negative relationship with respect to performance for both cap-weighted and fundamental-weighted portfolios (with the exception of sales). Fundamental indices however, outperform cap-weighted portfolios on a pre and post risk-adjusted basis. Despite the returns of fundamental indices responding positively to size and value premiums, the market risk premium is found to be more significant in explaining the return variations of the fundamental indices. The sales index is, however, the best performing fundamental index, displaying 4 significant findings:

i) A positive relationship between portfolio concentration and performance.

ii) A statistically significant Jensen's alpha.

iii) Lower than average beta.

iv) A statistically significant Fama and French alpha.

The equally weighted indices also outperform the cap-weighted indices, which is in line with the findings of Amenc et al. (2012) that if cap-weighted portfolios truly overweight overvalued stocks and underweight undervalued stocks due to the noise inherent in prices, then a simple non-price-weighting scheme will also outperform the cap-weighted index. However, according to Arnott et al. (2005) other non-price-weighting

schemes do not retain the up sides of the cap-weighted index, like fundamental indexation does.

3.6   Evidence from Emerging Markets

Research on fundamental indexation in emerging markets has not obtained as much popularity as in other markets but cannot be considered non-existent. Although research has been sparing in emerging markets hitherto, the results have not been an antithesis of other markets but rather provided added evidence in support of the superiority of fundamental indexation, with only minor differences in statistics. In 2011, research was performed on the JSE (South Africa) by Ferreira and Krige (2011), who investigated the relative performance of fundamental indices against their cap-weighted counterparts. Rather than having to recast a completely new approach to constructing the fundamental indices, Ferreira and Krige (2011) more or less recreate the technique originally used by Arnott et al. (2005). The fundamental variables used are sales, book value, cash flow and dividends. By ranking companies according to their magnitude of fundamental variables, the top 1000 are selected to construct the FTSE/RAFI 1000 index, in conformity with traditional use. The JSE ALSI acts as a proxy for the cap-weighted benchmark. Ferreira and Krige (2011) also construct a RAFI composite index based on the average values of the fundamental variables.

Their findings reveal that, over the test period from 1996 to 2009, the RAFI composite index outgrew the FTSE/JSE ALSI. Whilst both indices begin with identical values of 5598.73, the RAFI composite and FTSE/JSE ALSI end with values of 41966.17 and 24932.27, signifying cumulative returns of 649.57% and 345.32% respectively. The fundamental indices outperform the cap-weighted indices in 12 out of the 14 years examined, with only 2007 (-1.51%) and 2008 (-1.19%) displaying an underperformance in terms of returns. Reasons advanced for the underperformance is related to crisis in the Asian markets, which resulted in stock pricing being driven primarily by growth. However, on a compounded returns basis, the RAFI composite ekes out average excess returns of 5.55% in all the 11 years. The four individual indices also outperform the FTSE/JSE ALSI both on a return and risk-adjusted return basis throughout the period, with dividends being the highest performing fundamental index (6.52% per annum).

Amazingly, the RAFI composite index yields lower turnover cost (17.04%) relative to the FTSE/JSE ALSI (17.13%).

Other researchers [6](Estrada, 2008) who included emerging markets in their research have uncovered evidence of the lofty performance of fundamental-indexed portfolios relative to their cap-weighted counterparts. Arnott and Shepherd (2009) show that fundamental indexation has even greater potential to add value in developing markets where mispricing and market inefficiency is more pronounced. Because emerging markets are much less efficient than their developed counterparts, the return drag on cap-weighted indices is much greater, creating more opportunities for generating excess returns through fundamental indexation. Arnott and Shepherd (2009) highlight the fact that higher growth prospects in developing/emerging markets also allow for greater diversification. By analysing the growth of a dollar across the period January 1994 through December 2009, Arnott and Shepherd (2009) realise that the emerging market RAFI index adds more value than the cap-weighted counterpart (FTSE AW index). The value added increases with the noisiness of the market.

Recent research by Dibanisa Fund Managers (2013), who use identical fundamental variables and methodology, produce confirmatory results. They test the relative performance of the FTSE/JSE RAFI ALSI capped index to that of the FTSE/JSE ALSI capped index and FTSE/JSE SWIX. The FTSE/JSE RAFI ALSI capped index outperforms both cap-weighted indices over the period from 31 January, 2002 to 31 March, 2013 by an average of 1.65%, with significantly higher excess returns in bull markets and slightly higher excess returns in bear markets. Throughout all rolling periods (1, 3 and 5 years), both tracking error and information ratios are also dominant for the FTSE/JSE RAFI ALSI capped compared to the cap-weighted comparatives.

The results of the performance of fundamental indices against cap-weighted indices in emerging markets has proven to be in line with the predictions of Arnott and Shepherd (2009), who predicate better performance of fundamental indices because of the

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[6] Estrada (2008) included South Africa and Singapore in the research sample. Although considered developed economies by the J.P. Morgan Chase and United Nations classification indices, both countries are nevertheless still held as emerging economies by the Morgan Stanley Capital International's emerging-market index.

likelihood of greater mispricing as a result of possibly more perverse market inefficiencies. Hsieh (2013) also performs research on emerging markets to investigate the relative performance of fundamental indices against cap-weighted indices and finds corroborating evidence of the superior performance of fundamental indexation, with performance driven primarily by the market and value premium. However, Lobe and Walkshäusl (2008) find that when the results of the fundamental indices are subjected to a robustness test, only 3 out of 11 emerging markets examined generate excess returns that are statistically significant. The results could be indicative of the fact that whilst fundamental indexation is probably more beneficial in emerging markets, the results may not be robust in most emerging markets.

3.7 The Uniqueness of Fundamental Indexation and the Persistence of its Performance

The boundless debate on the subject of whether or not fundamental indexation is a unique or novel investment strategy and doubts about the persistence of its performance has enlivened much interest in the concept. The main aspects of the debate have revolved around the issue of fundamental indexation masquerading itself as a novel and passive strategy when it is, in fact, a value and an active investing strategy. When it comes to persistence in performance, the performance is only likely to endure if it is driven by something more perceptive than just noises in stock prices.

3.7.1   Uniqueness of Fundamental Indexation

Fundamental indexation has been heavily linked to value investing by researchers such as Asness (2006) and Bogle and Malkiel (2006), who claimed that this alleged new indexing strategy is simply a particular repackaging of quantitative value investing. Even worse, Blitz and Swinkels (2008) argue that, because fundamental indexes are fashioned to benefit from value premium - making it a one-factor quantitative strategy - multifactor quantitative strategies are better off in terms of relative performance since they are able to benefit from other documented anomalies. Arnott and Hsu (2008) and Arnott, Hsu, Liu & Markowitz (2010) illustrate how size and value are natural occurrences whenever market prices are defined as fair value plus mean-reverting pricing error.

Arnott, Hsu, Li and Shepherd (2010) perform research on fixed income assets to investigate the claim that value and size are the drivers of the performance of fundamental indices. They use fixed income assets because value and size are not important risk factors for bonds. In addition, fixed income risk factors are generally considered idiosyncratic and distinct from equity risk factors. So if the fundamental indices constructed from fixed income assets outperform their cap-weighted counterparts, then the performance of fundamental indices is hardly driven solely by value and size risk premia. The results of the study show that the outperformance of fundamental indices is driven by and large by superior security selection, and, secondly, the performance gap increases with increasing inefficiency in the market. Arnott et al. (2010) also find that during bear markets, fundamental indices in emerging markets (which are less efficient) experience underperformance relative to the cap-weighted index. Hsieh (2013), who performs research on emerging markets, finds that fundamental indexation might be exposed to known risk factors during turbulent times in such markets.

Bernstein (2006) attributes two-thirds of the performance to priced risk factors and a third to the uniqueness of the technique. He however stamps a caveat, stating that the superiority of the technique is not statistically significant and could be influenced by data mining. Fama and French (2010), on their end, illustrate that even though fundamental indices have a value effect inherent in their make-up, a Fama-French (1993) three-factor regression reveals a net alpha of -0.1% but value indices earn an approximate Fama and French alpha of -1.5% or worse.

Arnott et al. (2005) assert that even though fundamental indexation might be somewhat attributable to the investment characteristics of certain style investment and active management techniques, it has the unique quality of retaining most of the upsides of a cap-weighted indexing mechanism.

3.7.2   Persistence of Performance

The "Schwert Rule" introduced by William Schwert (2001) translates into the understanding that anomalies often disappear, reverse or attenuate after having been documented and analysed. Fundamental indexation is well founded on the principle of

stock mispricing and the subsequent mean reversion of the prices of such stocks. Edesess (2008) questions the persistence in performance of fundamental indexation after the inefficiency in the market, to which it is exposed, is reversed. He argues that the observed outperformance of fundamental indexation will be arbitraged away with subsequent stock price correction or reversal. Malkiel (2003) is of the view that even though markets may be vulnerable to pricing mistakes, winning performance is a "zero sum" game, since mispriced stocks at either end are bound to be held by investors on opposite sides of the spectrum. The father of value investing, Benjamin Graham (1965), highlights that, while the market may act as a voting machine in the short run, it nevertheless is a voting machine in the long run. The above arguments simply point to the fact that the market eventually corrects/reverts its temporary mispricing.

Hsieh (2013) states that as long as mispricing in stocks is not persistent, mean reversion towards the intrinsic value of stocks will create a return drag in the performance of cap-weighted indices due to misplaced assignment of weights to undervalued and overvalued stocks. It is this return drag that precipitates the persistence of the performance of fundamental indexation. Since markets are doomed to suffer mispricing at one time or another or in a particular sector of the market, fundamental indexation will, over time, exhibit superior performance.

Arnott et al. (2005), amongst other researchers, also document the persistence of the performance of fundamental indices across bear and bull markets. Some researchers (Arnott et al., 2010) have seen an alternation in performance across market cycles. In the light of the criticism by Amenc et al. (2012) on the issue of lack of theoretical guidance on the choice of accounting parameters to be used in constructing fundamental indices - which could well lead to data snooping - for improved and persistent performance, Stotz et al. (2010) recommend the use of a composite index, which minimises the valuation mistakes and volatility inherent in a single fundamental variable. Blitz et al. (2010) advocate for a blended index, with different rebalancing dates. Evidence points to the fact that even though fundamental indexation might have underperformed during certain charted business cycles, the technique has proven to be persistent in generating superior performance, triggered by the market mispricing and subsequent reversal of mispriced stocks to their intrinsic values.

3.8   Conclusion

Research on fundamental indexation has been pervasive in terms of its examination and application across markets. The concept, originally conceived by Arnott et al. (2005) has been heavily criticised, yet advocates of the concept have tested its feasibility and plausibility across the world and provided ample evidence of its superior performance over and above the cap-weighted portfolio. While some researchers (Hemminki and Puttonen, 2008; Hsu and Campollo, 2006) simply replicate the model in the U.S. and alternative markets, other researchers have extended the test procedure and even introduced novel weighting and nuance differences in its application.

Chen et al. (2007) derive fundamental values by smoothing cap weights while Estrada (2008) reveals that cross-border application of fundamental indexation was insignificant in increasing international diversification. Hsieh et al. (2012) find that, unlike fundamental indices, the performance of cap-weighted portfolios, constructed from global markets, are negatively affected by increases in portfolio concentration while Hsieh (2013) finds that both fundamental indices (except sales) and cap-weighted portfolios constructed from a conglomerate of emerging markets exhibit a negative relationship between performance and portfolio concentration.

The performance of fundamental indexation in emerging markets has been observed to soar and generate alphas a lot higher than in developed markets. This observation has been ascribed to the higher level of market inefficiency in emerging markets, causing stocks to be vulnerable to mispricing and subsequent reversals.

In spite of the performance of fundamental indices being partly driven by factor risks premiums, this investment technique and weighting methodology has demonstrated its unique ability to retain the benefits of cap-weighted indices while still generating alphas with longer persistence across markets.

Chapter 4 : DATA AND METHODOLOGY

4.1   Introduction

Having discussed the theories underlying capital asset pricing and fundamental indexation in chapter two and also the empirical literature surrounding the concept of fundamental indexation in chapter three, this chapter sets out to discuss the data and methodology applied in this research. The chapter begins with a brief review of the research problem. Furthermore, the rationale for, as well as a description of, the data employed in this research and possible research biases are presented. Moreover, steps taken to mitigate the biases are explained. Finally the index construction methodology and portfolio formation techniques are described.

Before delving into the data and methodological aspects of this research study, a quick review of the research problem, as discussed in chapter one, is presented below.

Q_1: Are fundamental indices, constructed from the Taiwanese top 50 and mid-100 stocks, more mean-variance efficient than cap-weighted indices?

Q_2: Does the smoothing of stock prices mitigate stock price volatility and, therefore, reduce the return drag inherent in cap-weighted indices as a result of speculative prices and misplaced weights?

Q_3: Is fundamental indexation a distinctive indexation methodology and are its returns statistically significantly influenced by style risks premia? If they are, do fundamental indices still generate positive alphas after accounting for style risks premia?

Q_4: Is the performance of fundamental indices more robust or resilient than that of cap-weighted indices in both bull and bear market cycles.

As mentioned earlier, we contextualise the research problems above in the following order:

Q_1: Mean-variance efficiency of fundamental indices relative to cap-weighted portfolios.

Q_2: Relative performance of Smoothed Cap Weights.

Q_3: Performance Attribution of fundamental indices.

Q_4: Performance Robustness of fundamental indices.

4.2   Data and Sample Selection

Despite being established in 1961 and set rolling a year later, the TWSE, like most stock exchanges in emerging economies, faced the challenge of procuring and maintaining a comprehensive and reliable database of financial and corporate data for its listed companies. While the data is not outright unreliable, the inconsistent nature of the available data casts a shadow of skepticism on its usability. Although electronic data was available from the early 90s, more reliable and consistent data for listed companies only became available from 1995. Therefore the period chosen for this research runs from January 2001 to June 2014. This 162-month period (13.5 years) is considered long enough to investigate the swings in returns for the alternate weighting techniques being evaluated and also test their performance in the different economic phases experienced in the Taiwanese equity market during the prescribed period.

The Taiwan Economic Journal (TEJ) databank has for many years served as the primary data provider for most of the major databases such as, DataStream International and Inet Bridge. Because of its wide coverage and extensive data history, and also because the most commonly utilised secondary databases like those named above - often used complementarily with one another - originate from the TEJ, the use of the TEJ databank as the only source of data for this research study still nevertheless validates its authenticity and reliability.

The TEJ database covers all publicly listed companies in Taiwan. The Taiwan Stock Exchange (TWSE) serves as the primary stock market and, as at May 2014, had 841 listed companies. There is also the over the counter market – The GreTai Securities Market (GTSM), where companies of; lower market capitalisation but impressive growth potential, lower profitability and relatively recent existence are listed.

4.3   Possible Research Biases and their Remedies

In order to ensure this research has plausible economic rationale and provide valid and unbiased results, the research data and sample periods have been carefully vetted. Cognisant of the fact that research findings are most often faulted by possible research biases, the most common biases and measures this research employs to cater for such

biases, in addition to previously discussed measures, are discussed below.

Data Mining Bias

This refers to the misuse of data, whereby data is repeatedly used to identify statistically significant patterns, which would otherwise be non-existent or insignificant. To guard against this bias, the researcher ensures that, firstly, significance tests levels are high enough in order to boost the validity of, and provide some degree of continuity to, the research findings. Secondly, in this research, the sample data is extended by 7 additional years of recent data; although not going as far back as that of the research of Lobe and Walkshäusl (2008). The inclusion of more than half a dozen years of recent data precludes possible overuse of previous data. Regression results are also analysed at 90%, 95% and 99% confidence intervals.

Sample Selection Bias (Survivorship Bias)

This bias occurs due to the absence of data, which leads to the exclusion of certain periods or variables from the research. One of the most common sample selection biases is survivorship bias. Survivorship bias is the tendency to overlook stocks that have failed to survive the entire research period. As previously stated, TEJ database is the primary data source for most renowned databases and has a wide constituency and greater reliability. Therefore it contains data on delisted shares, following their listing, up until their delisting date. The researcher minimises survivorship bias by including delisted stocks in the data sample up until the period of delisting.

Look-Ahead Bias

Because certain pieces of information about companies only become available much later after the year end, use of information that is not yet made public results in look-ahead bias. To avoid this bias, only data/information obtained from the published financial statements is used in constructing indices and analysis of index performance. Data related to the various indices are adjusted accordingly to reflect the relevant period.

Taiwanese companies are required to publish their monthly sales data on the 10th of the month following the relevant month. Therefore data relevant to the current month is

assumed to be made available only in the following month and is therefore pushed backwards to reflect it in the appropriate month. Sales data on the TEJ database is available on a monthly basis, as well as on a "last 12 months" basis. This research utilises the last 12 months cumulative value of sales and the necessary one month lag employed to cater for look-ahead bias.

Furthermore, the previous year's last quarter results and the current year's first quarter results for book value and earnings of Taiwanese companies are required to be published prior to the 20th trading day of April and the TEJ database updates company statistics on the 20th trading day of April. For the second and third quarter, publication of earnings and book value results must be published prior to the 20th trading day of June and September respectively. Quarterly dates for the availability of the book value and earnings are shown in table 4.1 below.

Therefore, in order to mitigate look-ahead bias, data for book value and earnings for the months falling within the first quarter of the current year and last quarter of the previous year are assumed to be available only on the 20th of April of the current year but recorded in the relevant months. Equally, data for these variables for the months within the second quarter are assumed to be available only on the 20th of June and data for book value and earnings for the third quarter are recorded in the relevant months but assumed to be available on the 20th of September. The published data, however, is only available in the form of book value per share (BVPS) and earnings yield (EY). Some adjustments are, therefore, required to reflect the NT$ amounts, which is shown later.

Table 4.1: Book value and Earnings Quarterly Data

Quarter	Relevant Dates
1	April, 20
2	June, 20
3	September, 20
4	April, 20 (Following year)

Because dividends are only made available to the public when published, dividends needed no adjustments. The total dividends represent all the dividends declared in the last four quarters. That is, the total annual dividends.

Time Period Bias

To ensure that performance is not driven solely by mere swings in economic cycles, testing data spanning different phases of the economy provides a more realistic view of the relative performances of the weighting measures being evaluated. The sample period chosen encompasses different phases, from the aftermath of the burst of the information technology bubble of 2000, through sub-prime crisis which led to the crash of financial markets in 2008 up until the dip in stock markets of August 2011. Interjecting these periods have been episodes of bull and bear market cycles, allowing for a comparative performance across the different economic phases of the Taiwanese market. This removes any time-period specificity from the results, giving a more accurate picture of the intended investigation.

4.4   Research Methodology

In order to meaningfully investigate and standardise the mechanics and results of this research with that of previous research on this market, this research employs the methodology that Lobe and Walkshäusl (2008) used. Coincidentally, their methodology is in sync with that of Arnott et al. (2005). This methodology is applied in the construction of cap-weighted reference portfolios and fundamental weighted portfolios, for different metrics of size, and a fundamental composite index. The measures of size for the fundamental indices are sales, earnings, book value and dividends. Lobe and Walkshäusl (2008) use payout yields instead of the dividends yield under the argument that payout yields are stronger predictors of returns of firms in time series analyses. This research sticks with the dividends yield, as the dividends metric generated the lowest risk, measured by standard deviation, and sometimes relatively higher risk-adjusted returns in most of the previous research on fundamental indexation (Arnott et al, 2005; Ferreira and Krige, 2008).

A cap-weighted index weights stocks based on their market capitalisation. A fundamental index, also described as a main street measure, weights stocks on the basis of the value of the corresponding fundamental metric of size. The fundamental value is more indicative of the economic potential of the stock (Arnott et al., 2005; Hsu, 2006).The cap-weighted index of the TWSE is the Taiwan Stock Exchange Capitalisation Weighted Stock Index (TAIEX), constituting all listed stocks, weighted by their market capitalisation. The only stocks excluded are preferred stocks, stocks listed for less than one calendar month and full-delivery stocks.

The methodology employed in developing the indices, and performing the analyses in this research study entails:

Step 1; the cap-weighted benchmark index is determined. The cap-weighted benchmark used for this research is the TAIEX, with its monthly and annual performance available on the TWSE website. In addition to the market proxy (TAIEX), this research also employs a cap-weighted reference portfolio constructed under a similar methodology as the fundamental indices described below. The purpose of constructing a cap-weighted reference portfolio, as opposed to just utilising the TAIEX, is to allow for a more reasonable, equitable and practical comparison.

Step 2; derive and rank the fundamental metrics. Fundamental metrics for each company (stock) are obtained from the TEJ database by analysing the financial records of each company. In constructing the individual fundamental indices, the average of the trailing three year values is used but in the absence of trailing three year (36 months) data, the average of the number of years' data available is used. Although Arnott et al. (2005) used a trailing 5-year average, their research did highlight the fact that there was no significant change in the results of the fundamental indices based on either a trailing 5-year or 3-year average. Moreover, the very high volatility predominant in the Taiwanese market does not necessitate the historical long term average windows applied in other research. The most recent 12 month values are more relevant and a 36-month moving average is, therefore, satisfactory. The fundamental indices constructed are the sales index, dividends index, book value index and the earnings index.

Taiwanese dollar (NT$) values for sales are available for the individual stocks on a monthly, quarterly and annual basis, as well as the cumulative sales figure for the last twelve months. The cumulative sales figure for the last 12 months is employed as it contributes in smoothing out the possibly large discrepancies in monthly sales. However, book value, earnings and dividends are not reflected in monetary values but as ratios - that is, book value per share (BVPS), earnings yield (EY) and dividends yield (DY). In order to obtain the NT$ values for book value, earnings and dividends, the following calculations were performed:

$$Book value = BVPS * Number of shares \qquad 4.1$$
$$Earnings = EY * Price * Number of shares \qquad 4.2$$
$$Dividends = DY * Price * Number of shares \qquad 4.3$$

By applying the monthly number of shares and price to the ratios of the variables, the appropriate NT$ amounts for each month are obtained.

Despite utilising last 12 months' cumulative sales values but monthly figures for some of the other size metrics, the technique does not significantly influence the weights assigned to individual stocks as all stocks are weighted based on their cumulative sales value and monthly values for other metrics of size. After obtaining these metrics, securities are ranked, for each metric, based on the value of each of the four fundamental metrics and the top 50 and mid-100 stocks by metric value are selected. Index rebalancing of the stocks is done on a monthly basis.

Step 3; determine the fundamental metric weights and construct the fundamental composite index. The weight of each stock for each metric is ascertained in order to determine the weighted metric returns by applying the proportionate weights to the corresponding stock returns. The weight of each fundamental metric for each stock is calculated based on the formula below,

$$W_{k,i,t} = \frac{Max[0, F_{k,i,t-1}]}{\sum_{i=1}^{N} Max[0, F_{k,i,t-1}]} \qquad 4.4$$

Where:

W   is the weight of security i, for the fundamental metric k at time t;

$F_{k,i,t-1}$ is the value of the metric k for stock i at time t-1;

k   is the fundamental metric being considered;

i   is the stock/company;

t-1   signifies the period just ended; and

N   represents the total number of stocks constituting the portfolio concentration (which would be either 50 or 100).

Utilising the weights of the period just ended (t-1) and matching them with the returns of the current period (t) minimises look-ahead bias. The returns at the end of period t are based on the weights of the variables of period t-1. So the returns of period t have to be pushed back to period t-1, as they relate to the variables of t-1 and not period t.

Likewise, the weight of the constituents of the cap-weighted reference portfolio for inclusion in the current period is found using Formula 4.5 below.

$$W_{i,t}^{cap} = \frac{P_{i,t-1}S_i}{\sum_{i=1}^{N} P_{i,t-1}S_i} \qquad\qquad 4.5$$

Where:

$W_{i,t}^{cap}$ is the weight of stock i at time t, weighted by its market capitalisation;

$P_{i,t-1}$ is the price of stock i at period t-1;

i   is the individual stock;

t   is the current period;

t-1   is the period just ended; and

S_i is the number of shares of stock i.

The fundamental composite index is constructed based on the average of the four fundamental metrics (book value, earnings, dividends and sales). A company's fundamental composite weight, r_i, is defined as the average weight of the four fundamental variables. In the case where less than four fundamental metrics of size are available, the fundamental composite index is constructed from the average weight of the fundamental variables available. Table 4.2 below provides the average number of

securities which had 4, 3, 2, 1 and 0 securities throughout the research sample period and Equation 4.6 illustrates how the average weight is calculated. From Table 4.2 below, it can be seen that more than 50% of the securities had at least 3 fundamental metrics available throughout the research period.

r_i = [weight of (Sales + Dividends + Book value + earnings) /4]   4.6

Table 4.2: Depiction of Fundamental Metric Representation

Number of fundamental metrics available	Average number of securities	Percentage representation
4	243	15.8%
3	639	41.6%
2	180	11.8%
1	186	12.1%
0	287	18.7%
Total	**1535**	**100%**

Step 4; the monthly returns of each security is derived. The monthly return for each security is derived by finding the ratio of the end value as a fraction of the beginning value minus 1.

$$\text{Monthly Return \%} = \frac{\text{Current month}'s\ value}{\text{Previous month}'s\ value} - 1 * 100 \qquad 4.7$$

The derived return is used for constructing both the fundamentally-weighted and cap-weighted portfolios. The TWSE, however, provides the returns for each stock listed on the exchange. Therefore the necessity of doing the return calculation is redundant.

Step 5; portfolio concentrations for fundamental indices and cap-weighted reference portfolio are constructed. Portfolios of various concentrations (Top 50 and mid-100) are constructed for both the fundamental indices and cap-weighted reference portfolio. In constructing the portfolios the following steps are followed:

- A ranking of the securities based on their fundamental variables determined in step 2 is done. For the Cap-weighted reference portfolio, the securities are also ranked based on their closing market values (market capitalisation). After ranking, the top 50 and mid-100 stocks are chosen based on the relevant portfolio concentration being constructed.
- The proportion that each security bears on the total value of all securities that rank amongst the top 50 or mid-100 stocks is determined. Proportions for fundamental portfolios are based on fundamental values while the cap-weighted reference portfolio is based on the market capitalisation of the securities.
- The product of the weight of each security and its return obtained in step 3 is determined and the monthly weighted returns for all stocks constituting the relevant index are summed. These monthly returns represent the monthly returns for each of the portfolio concentrations. The procedure is repeated for each month of the research period.

Step 6; construct the SCW index. The market prices for a fixed window of the immediate past (12 months) are smoothed by finding the median share price. Based on the median share prices, the median weight is determined by multiplying the median share prices by the corresponding number of shares (to get the median market capitalisation) and applying equation 4.5 above. Chen et al. (2008) revealed that the length of the smoothing window period has little or no effect on the subsequent results. So this research limits smoothing to a 12-month window.

$$\text{Median weight} = \frac{6th + 7th}{2} \qquad\qquad 4.8$$

Adjustment of the SCW is made to accommodate corporate events such as mergers, acquisitions or spin-offs, whereby the resultant company is treated as a new company. Because the SCW is simply found by ranking the weights and finding the median, little rebalancing would be required for the smoothed capitalisation weighting. The SCW is then applied to the monthly stock returns to obtain their respective weighted monthly returns.

Step 7; analysis and regression of the results are made. The regression of the returns of

the fundamental indices using the Fama-French (1993) 3-factor model indicates the sign and level of significance, if any, at which the returns of the fundamental indices show a factor loading on the small cap and value risk premia.

In determining the size risk premia (SMB) for the Fama-French (1993) 3-factor model, the average monthly returns of the stocks that form the top 20 percentile by market capitalisation are deducted from the average monthly returns of stocks constituting the bottom 20 percentile by market capitalisation. Value risk premia (HML) are determined by subtracting the average monthly returns of stocks that constitute the bottom 20 percentile, measured by book-to-market ratio (B/M), from the average monthly returns of stocks that constitute the top 20 percentile, measured by B/M ratio.

The monthly returns obtained are analysed in terms of annualised arithmetic and geometric returns, as well as risk-adjusted returns. The annualised returns are derived by annualising the average monthly returns generated over the entire examination period using the formula:
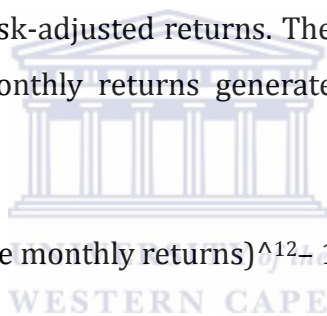
Annualised returns = $(1 + \text{average monthly returns})^{12} - 1$ 4.9

The monthly standard deviation for each portfolio concentration is found and annualised

Annualised volatility = Monthly standard deviation $* \sqrt{12}$ 4.10

Although index rebalancing in this research is performed on a monthly basis, returns for the fundamental indices are not adjusted for transaction cost for two reasons: Firstly, the high liquidity and high level of market concentration in the Taiwan equity market reduces the need, in practice, to frequently rebalance stocks. Secondly, the construction of portfolios, as opposed to analysing individual stocks, greatly reduces the level of rebalancing that is required, as very few securities lose their rank in the originally constructed portfolio.

Risk-adjusted returns based on the Sharpe ratio, Treynor measure, M-squared and

Information ratios are also computed. The Sharpe ratio measures the excess return of the portfolio over the risk-free rate, discounted against the standard deviation. The Treynor measure determines the excess return of the portfolio over the risk-free rate but is discounted against the systematic risk only – beta - (Hsieh and Hodnett, 2013). The M-squared evaluates the performance of a portfolio that is equally leveraged as the market proxy, against the performance of the market proxy. The Information ratio provides a direct measure of the relative performance of the assessed portfolio against its benchmark (Hsieh and Hodnett, 2013). In this research, the benchmark index is the cap-weighted reference portfolio (not the TAIEX).

Beta coefficients, based on time-series regressions, are determined and Jensen's alphas are computed using the CAPM regression equation (4.11) below.

$$E(R_{i,\,t}) - R_{f,t} = \alpha_i + \beta_i * (R_{m,t} - R_{f,t}) + \varepsilon_{i,t} \qquad\qquad 4.11$$

Where:

$E(R_{i,\,t})$ is the expected/realised return on index i in month t;

$R_{f,t}$ is the yield on the 3-month Taiwanese Treasury bill in month t;

$R_{m,t}$ is the TAIEX return in month t;

β_i signifies the sensitivity of the excess returns of index i to movements in the market risk premium;

α_i is the Jensen's alpha for index i; and

$\varepsilon_{i,t}$ is the regression residual in month t.

Index i represents any of the indices, other than the TAIEX, and the risk-adjusted values are computed for fundamental indices, the reference portfolio and the SCW index.

Maximum drawdown and cumulative returns of the different weighting metrics are also found. The maximum draw down, which represents the maximum loss incurred by each index over the entire research period, indicates the loss potential of the different weighting metrics, as well as the loss potential of the various indices.

For performance attribution, this research utilises the Fama-French (1993) 3-factor

model and employs the methodology of Hsieh (2013) to examine the sensitivities of fundamental indices to the proxies for factor risks within the model. A regression of the monthly returns of the fundamental indices (top 50 and mid-100) against the Fama-French (1993) 3-factor model sheds light on whether or not fundamental indices are unique investment styles. The determination of whether or not fundamental indices are a distinctive investment methodology lies in the sensitivities of their returns to the movements in the returns of the factor risk proxies of the Fama-French (1993) 3-factor model (Hsieh, 2013). Equation 4.12 below illustrates the Fama-French (1993) 3-factor model.

$$E(R_{i,\,t}) - R_{f,\,t} = \alpha_i + \beta_{i,\,m}(R_{m,\,t} - R_{f,\,t}) + \beta_{i,\,HML}(HML_t) + \beta_{i,SMB}(SMB_t) + \varepsilon_{i,\,t} \qquad 4.12$$

Where:

$E(R_{i,\,t})$ is the expected/realised return of index i at time t;

$R_{f,\,t}$ represents the risk-free rate at time t;

$\beta_{i,\,m}$ signifies the sensitivity of the excessreturns of indexi relative to the market risk premium;

$\beta_{i,\,HML}$ signifies the sensitivity of the returns of indexi to movements in the value risk premium;

$\beta_{i,SMB}$ signifies the sensitivity of the returns of index i to movements in the size risk premium;

HML_t represents the excess return generated by stocks comprising the top 20th Percentile weighted by B/M ratio (high book value) over stocks comprising the bottom 20th percentile by B/M ratio (low book value) from the sample;

SMB_t represents the excess return generated by small-cap stocks (bottom 20th percentile) over large-cap stocks (top 20th percentile) from the sample;

α_i represents the Fama and French alpha; and

$\varepsilon_{i,t}$ signifies the Fama-French regression residual.

The term "$E(R_{i,\,t}) - R_{f,\,t}$" signifies index i's excess return over the risk-free rate and the multiple regression of $E(R_{i,\,t}) - R_{f,\,t}$ against the terms $R_{m,\,t} - R_{f,\,t}$, HML_t and SMB_t produces slopes equal to their respective betas and an intercept equivalent to the Fama-French alpha.

In evaluating the robustness of the returns of the fundamental indices against the market proxy and reference portfolio, the market is segmented into bear and bull market cycles. The determination of the bull and bear market cycles and other influences on the Taiwanese market are discussed in chapter 7 of this research stud

4.5   Conclusion

From the outset of this chapter, the revolutionary events that led to the liberation of Taiwan from pre-colonial influences are discussed. Despite going through the travail of multiple colonial regimes, coupled with stiff restrictions on foreign trade, limited trading hours and ceilings on price movements and derivative transactions, the TWSE managed to climb the ranks of trading activity and became one of the largest stock exchanges in terms of transaction volumes. However, far recent events have led to the market losing over three-quarters of its market capitalisation. Although some substantial recovery has been made in terms of regaining its market capitalisation, recent events have triggered a (an imminent) downgrade of the Taiwanese stock market to the status of an emerging market.

Prior research on fundamental indexation on the Taiwanese equity market evidenced the lack of a mean-variance-efficient fundamental composite index, relative to the cap-weighted index. The recent reclassification of this market provides the motivation for this research study. The research question and objectives are also outlined. Finally, this chapter describes the data and sample period, together with the methodology employed in constructing the fundamental indices and the reference portfolio, as well as the techniques used in the analyses of the results of the indices.

Chapter 5 : PERFORMANCE EVALUATION OF FUNDAMENTAL INDICES

5.1   Introduction

Having discussed the methodology applied in this research in the previous chapter, this chapter sets out to present the results of the investigation of the relative performances of the different indices. This chapter evaluates the basic return, the risk and the risk-adjusted performance of the different fundamental indices investigated, as well as comparative benchmarks. The results for the fundamental indices of the top 50 stocks are initially discussed, followed by that of the mid-100 stocks and a comparative analysis of the portfolios of different concentrations (top 50 and mid-100) is made.

In analysing the return characteristics of the top 50 and mid-100 indices, the basic return statistics employed are the arithmetic return, the geometric return, as well as the cumulative return of the different indices. The raison *d'être* for the different return measures rests on the fact that each of these measures describes a particular property of the index's performance. While the arithmetic return simply presents the annualised returns (mean return) of the indices over the period of investigation, the geometric return denotes the annual growth rate of the index throughout the period. The cumulative return, on its part, depicts the cumulative growth of the index's return over the period. The cumulative returns indicate the growth of a hypothetical amount; say a rand, invested in each of the indices over the examination period

In evaluating risk, the standard deviation, beta and maximum drawdown are used. The standard deviation measures the average deviation of the index's periodic returns from the index's mean return while the beta measures the sensitivity of the index returns with respect to movements in market returns. The maximum drawdown describes, as a percentage, the maximum loss incurred by the different indices over the course of the examination period.

For risk-adjusted return measures, the Sharpe ratio, Treynor measure and Information ratio, together with the Jensen's alpha and M-squared are employed. These measures are discussed in the methodology of this research and will be expounded on accordingly.

The superior performance of fundamental indices has been historically linked partly to the mean reversion of overvalued/undervalued cap-weighted stocks to their intrinsic (mean) value, causing a return drag in cap-weighted portfolios (Shiller, 2005; Siegel, 2006). Ultimately, the relative performance of the fundamental indices against the cap-weighted reference portfolio and the TAIEX would provide some evidence of the level of mean reversion inherent in stocks of the Taiwan equity market. The mean-variance efficiency of the fundamental indices relative to the cap-weighted indices relays information on the level of mean reversion inherent in Taiwanese stocks.

5.2   Performance of the Top 50 Indices

5.2.1   Basic Return Statistics.

Table 5.1 displays the basic return, risk and risk-adjusted return performance of the top 50 indices.

The sales index displays the highest arithmetic return of 12.23%. Its sturdy arithmetic return is followed by the fundamental composite index with a value of 10.70%. The market proxy displays a mean return of 8.13% while the cap-weighted reference portfolio shows a much softer arithmetic return of 5.76%. On average, the fundamental indices constructed from the top 50 stocks, excluding the smoothed cap weighted (SCW) index, generate an arithmetic return of 9.48%, which is 1.35% in excess of the market proxy and 3.75% in excess of the reference portfolio. The SCW index, although not technically a fundamental index but considered as one in this research is excluded from the above comparison in order to explore how the fundamental indices, based on accounting variables, performed. The SCW index generates the lowest arithmetic return of all the fundamental indices but still outperforms the reference portfolio by 0.77%. Upon including the SCW in determining the average return of all fundamental indices, an average return of 9.0% is obtained.

The inclusion of the SCW index in finding the average fundamental index return slightly shrinks the excess return of fundamental indices on the market proxy and the reference portfolio to 0.9%and 3.26% respectively.

Table 5.1: Basic Performance Statistics for Top 50 Stocks									
	Market Proxy	Risk Free rate	Reference Portfolio	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fundamental Composite Index
Return									
Arithmetic Return	8.13%	1.30%	5.76%	6.53%	8.69%	8.59%	7.35%	12.23%	10.70%
Geometric Return	2.77%	0.01%	2.17%	2.61%	4.07%	4.56%	3.60%	8.96%	6.82%
Cumulative Return	1.982	1.001	1.335	1.417	1.713	1.825	1.613	3.184	2.437
Risk									
Standard Deviation	23.68%	0.03%	26.53%	27.76%	29.92%	27.96%	26.89%	24.68%	27.15%
Beta	1.000	N/A	1.085	1.124	1.152	1.112	1.076	1.005	1.060
Max. Drawdown	-56.26%	-	-56.84%	-60.80%	-56.49%	-54.35%	-57.06%	-52.94%	-52.30%
Risk-adj. returns									
Sharpe Ratio	0.289	N/A	0.168	0.189	0.247	0.261	0.225	0.443	0.346
Treynor Ratio	0.068	N/A	0.041	0.046	0.064	0.066	0.056	0.109	0.089
Jensen's Alpha	0	N/A	-2.95%	-2.46%	-0.48%	-0.31%	-1.30%	4.06%	2.16%
Information Ratio	0.345	N/A	N/A	0.209	0.302	0.428	0.257	0.852	0.604
M-squared	0	N/A	0.053	0.058	0.071	0.075	0.066	0.118	0.095

The dividends index is the worst performer of the fundamental indices formed from accounting variables, with an arithmetic return of 7.35%, falling short of the return of the market proxy by 0.78% but outperforming the reference portfolio by 1.59%. Arnott et al. (2005) also identified the dividends index as the lowest return generating fundamental index. The dividends index, constructed by Arnott et al. (2005), however, outperformed the reference portfolio and market proxy but was not constructed from only the top 50 stocks. The earnings index and book value index show returns of 8.59% and 8.69% respectively, both of which outperform the market proxy. It is interesting to note that, with the exception of the dividends index and the SCW index, all fundamental indices comprised of the top 50 stocks outperform the market proxy in terms of arithmetic returns. With regards to the reference portfolio, all fundamental indices generate higher arithmetic returns relative to the reference portfolio.

Despite being much more discounted, the geometric returns follow a similar performance pattern to that of the arithmetic returns above but reflect much more insightful information in terms of the growth rate of the different indices over the period of investigation. On the basis of geometric return, all fundamental indices of the top 50 stocks, with the exception of the SCW index, outperform the market proxy and the reference portfolio. Even the dividends index, which revealed a lower arithmetic return

than the market proxy, generates a higher geometric return of 3.60% compared to the 2.77% of the market proxy. Again the sales index leads in terms of portraying the highest geometric return with a value of 8.96% and the fundamental composite index shadows the sales index with a geometric return of 6.82%. The SWC index reveals a geometric return of 2.61%, which is 0.16% lower than that of the market proxy.

There appears to be a rather large rift between the arithmetic and geometric returns of the investigated indices above. The large chasm between the arithmetic and geometric returns is triggered by the high levels of standard deviation in the returns of the respective indices. The higher the standard deviation of the index monthly returns, the greater the discrepancy the arithmetic and geometric returns will be. Upon examining the standard deviations of the fundamental indices later in this chapter, a better understanding of these differences will be obtained.

Table 5.1 clearly denotes the superior performance of the sales index, exhibiting a cumulative return value of 3.184, followed by the composite index with a value of 2.437. In consonance with its lackluster arithmetic return and geometric return performance, the reference portfolio provides a footstool for all the other indices in terms of cumulative return, displaying a value of 1.335, while the SCW index tails all fundamental indices with a cumulative return of 1.417. The market proxy, which underperformed the book value index and earnings index in terms of the other two return characteristics discussed earlier (that is, the arithmetic and geometric return) now generates a higher cumulative return of 1.982 relative to the 1.713 and 1.825 for the book value and earnings indices respectively.

5.2.2   Risk Based Performance

Despite generating higher returns, fundamental indices do so at the expense of relatively higher absolute measures of risks. In terms of standard deviation, all fundamental indices (including the SCW, which generated lower returns than the market proxy) display higher volatilities; measured by the standard deviation. However, the sales index, which was the fundamental index with the highest returns, exhibits the lowest standard deviation relative to other fundamental indices, with only 24.68%, which is just slightly higher than the market proxy's 23.68% but lower than the reference

portfolio's 26.53%.

As mentioned earlier, the size of the discrepancy between the arithmetic and geometric return is accounted for by the magnitude of the volatility inherent in the index return. The relatively lower standard deviation of the sales index, with respect to other fundamental indices formed from the top 50 stocks, explains the narrower gap between its arithmetic return and geometric return.

The dividends index, which exhibits a volatility value of 26.89%, comes in second place after the sales index. As explained by Arnott et al. (2005), dividend-paying companies are mature and more stable companies. This accounts for the relatively lower volatility of the dividends index, despite its feeble returns. The fundamental composite index comes third with a standard deviation of 27.15%. Of the fundamental indices, the book value index displays the highest standard deviation (29.92%). All other fundamental indices exhibit higher standard deviations relative to the reference portfolio and market proxy. The lower volatility of the market proxy (24.68%) is accounted for by the higher level of diversification due to many more constituents in its constitution.

Subsequent to the stripping away of unsystematic risk, beta values exhibit slight differential patterns to their respective volatilities for the different indices. In comparison with other fundamental indices formed from the top 50 stocks, the sales index, in line with its all-round sturdy results, demonstrates the lowest beta of 1.005. This signifies that in terms of sensitivity to market movements, the sales index almost characterises the dynamics of the market but does so with higher returns being generated.

Contrary to the pattern observed in the volatilities of the single fundamental indices, the fundamental composite index reveals a lower beta value (1.060) than the dividends index (1.076). Although the dividends index is constituted of mature and more stable companies, the diverse constitution of the fundamental composite index, in terms of the accounting attributes used in its construction, has more than likely increased the diversification potential of the fundamental composite index; thereby lowering its beta. The book value index that previously exhibited the highest volatility, again maintains the

risk trend in terms of systematic risk with a beta of 1.152.

While examining the maximum drawdown, the sales index appears to have incurred a greater maximum loss than the fundamental composite index. The sales index incurred a maximum loss of -52.94%, which was higher than the fundamental composite index with a maximum loss of -52.30%. So the sales index incurred an excess loss of 0.64% over that of the fundamental composite index. The SCW index demonstrates an overall high of -60.80%, which is much higher than the maximum drawdown of the two conventional cap-weighted indices (market proxy, -56.26%: reference portfolio, -56.84%) constructed from a similar attribute – the share price. The dividends index, despite showing comparatively favourable values for standard deviation and beta, exhibits the highest drawdown (57.06%) of the fundamental indices based on accounting variables comprised of the top 50 stocks.

5.2.3   Risk-adjusted Performance

 The isolated assessment of an index on a return or risk measure alone falls short of a plausible assessment of its true performance. Relating return to the risk of a portfolio or to the benchmark it judges its performance against provides a more sensible assessment criterion.

The Sharpe ratio and the Treynor measure, which relate the excess return (over the risk-free rate) of the indices to their standard deviation and beta respectively, provide more intuition on how the different indices performed. Only the sales index and the fundamental composite index generate Sharpe ratios and Treynor measures that are higher than that of the market proxy. The Sales index reflects a Sharpe ratio of 0.443 and a Treynor measure of 0.109 while the fundamental composite index reveals a Sharpe ratio and Treynor measure of 0.346 and 0.089 respectively. The market proxy uncovers a Sharpe ratio and Treynor measure of 0.289 and 0.068 respectively.

Although the book value index and earnings index generate higher returns than the market proxy, these two fundamental indices underperform the market proxy in terms of Sharpe ratio and Treynor measure. This translates to the inadequate compensation for higher risks inherent in some of the fundamental indices of the top 50 stocks relative

to the market proxy. To corroborate this finding, the Jensen's alpha is negative for all but the two top performing fundamental indices (sales index and fundamental composite index), indicative of the fact that the returns generated by most fundamental indices are insufficient in terms of the returns required by the CAPM. All fundamental indices, however, show Sharpe ratios and Treynor measures, as well as M-squared values that are superior to that of the cap-weighted reference portfolio, which discloses a Sharpe ratio of 0.168 and Treynor measure of 0.046.

The Information ratio, which provides the most relevant measure of the performance of the fundamental indices against the reference portfolio, indicates that whilst all fundamental indices generated positive Information ratios, the sales index (0.852) and the fundamental composite index (0.604) again were the most consistent fundamental indices in outperforming the reference portfolio. Moreover, the earnings index, which generated a lower arithmetic return relative to the book value, now reveals a higher Information ratio of 0.261 compared to 0.247 for the book value index. This signifies that the earnings index achieves higher returns more efficiently - while taking on more risk - than the book value index.

The performance ranks of the Information ratio are repeated in the M-squared of the fundamental indices. The M-squared measure indicates the excess return of the fundamental indices over the market proxy under the assumption that the fundamental indices are leveraged at the risk-free rate to form a portfolio equally as risky as the market proxy. The results indicate that the sales index generates the highest M-squared of 0.118 and the fundamental composite index next in line with a value of 0.095. The reference portfolio shows an M-squared of 0.053.

5.3   Performance of the Mid-100 Indices

The presentation and discussion of the results of the fundamental indices composed of the mid-100 stocks follows a similar sequence as the top 50 indices discussed above. Table 5.2 provides a layout of the returns, risks and risk-adjusted returns of the fundamental indices of the mid-100 stocks and the respective benchmarks.

An overview of the arithmetic returns of the fundamental indices of the mid-100 stocks reveals much higher returns over and above those of their top 100 counterparts. A more detailed examination of the arithmetic returns reveals that, in consonance with the results of the fundamental indices of the top 50 stocks, the sales index of the mid-100 stocks generates the highest return of 19.48%. This is an 11.35% excess return over the market proxy, whose returns have not changed from those presented earlier. The market proxy generates an average arithmetic return of 8.13% while the revised cap-weighted reference portfolio – weighted on the basis of the market capitalisation of the mid-100 stocks – generates an arithmetic return of 9.50%. On the basis of the returns of the revised reference portfolio, the sales index exceeds the reference portfolio by an average return of 9.98%. This indicates that the sales index's arithmetic return more than doubles the return of the reference portfolio, as well as the market proxy. The fundamental composite index produces an arithmetic return of 17.85%. This again more than doubles the returns of the market proxy. The fundamental composite index generates excess returns over the reference portfolio to the value of 8.35%.

All fundamental indices of the mid-100 stocks outperform both the market proxy and the reference portfolio in terms of arithmetic returns. On average fundamental indices of the mid-100 stocks, excluding the SCW index, generate a return of 15.89%, which is 7.76% and 6.38% in excess of the market proxy and reference portfolio respectively. Because the performance of the SCW index is lower than the average return of all other fundamental indices, the combined average return of fundamental indices, inclusive of the SWC index, decreases to 14.98% but is still very much in excess of the reference portfolio and the market proxy.

Although the arithmetic returns of the SCW index of the top 50 stocks lagged behind the market proxy, the SCW index constructed from the mid-100 stocks generates an arithmetic return of 10.47%, which is 2.34% in excess of the market proxy and 0.97% in excess of the reference portfolio. The dividends index also recovered from its previous feeble returns, generating a return of 13.45% and, not only did it outperform the market proxy, it superseded even the returns of the earnings index (12.53%)that outperformed it during the review of the top 50 stocks. After the sales and fundamental composite

indices, the book value index was the next highest return-generating fundamental index of the mid-100 stocks with an arithmetic return of 16.13%.

Table 5.2: Basic Performance Statistics for Mid-100 Stocks									
	Market Proxy	Risk Free rate	Reference Portfolio	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fundamental Composite Index
Return									
Arithmetic Return	8.13%	1.30%	9.50%	10.47%	16.13%	12.53%	13.45%	19.48%	17.85%
Geometric Return	2.77%	0.01%	4.97%	5.85%	10.84%	8.01%	8.77%	14.90%	12.91%
Cumulative Return	1.446	1.001	1.926	2.154	4.011	2.829	3.113	6.520	5.152
Risk									
Standard Deviation	23.68%	0.03%	29.36%	29.62%	31.10%	29.02%	29.41%	28.48%	29.86%
Beta	1.000	N/A	1.157	1.190	1.186	1.148	1.160	1.123	1.175
Max. Drawdown	-56.26%	-	-63.96%	-63.98%	-62.37%	-59.59%	-60.19%	-57.26%	-59.30%
Risk-adj. returns									
Sharpe Ratio	0.289	N/A	0.279	0.309	0.477	0.387	0.413	0.638	0.554
Treynor Ratio	0.068	N/A	0.071	0.077	0.125	0.098	0.105	0.162	0.141
Jensen's Alpha	0	N/A	0.30%	1.04%	6.73%	3.38%	4.23%	10.51%	8.52%
Information Ratio	-0.123	N/A	N/A	0.208	0.664	0.506	0.728	1.537	1.029
M-squared	0	N/A	0.079	0.086	0.126	0.105	0.111	0.164	0.144

Following a drop in portfolio concentration, the fundamental indices of the mid-100 stocks demonstrate an impressive ability to grow their mean returns over and above the top 50 indices. The book value index of the mid-100 stocks, for instance, show a 7.44% increase in return over its top 50 counterpart while the sales index and composite index reveal 7.25% and 7.51% increases in returns respectively. The dividends index also showed an impressive 6.10% increase and the SCW index a 3.94% increase over their top 50 counterparts.

The geometric returns of the fundamental indices defend their sturdy mean return values. In fact, the geometric return of the sales index (14.90%) and fundamental composite index (12.91%) of the mid-100 stocks are more than twice that of their respective counterpart fundamental indices constructed from the top 50 stocks. Most of the other fundamental indices of the mid-100 stocks almost double the values of their

top 50 counterparts. This signals strong value-adding potential for constructing fundamental indices using the mid-100 stocks. The sales index and the fundamental composite index again occupy the lead positions in terms of the magnitude of their geometric returns. The book value index and dividends index follow the sequence with geometric returns of 10.84% and 8.77% respectively. The SCW index generates a lower geometric return of 5.85% while the reference portfolio, with a geometric return of 4.97%, lags behind all fundamental indices.

The rugged returns of the mid-100 fundamental indices are underpinned by their cumulative returns. The sales index displays the highest cumulative return throughout the period with a terminal value of 6.520, followed by the fundamental composite index (5.152) and the book value index (4.011). The market proxy (1.446), reference portfolio (1.926) and the SCW index (2.154) display the lowest cumulative return figures. This suggests that portfolios constructed from share prices – even the SCW index that was smoothed to avoid extreme share price deviations – are slow to accumulate returns. The other fundamental indices, constructed from accounting variables, follow the same performance sequence in accumulating returns as in generating arithmetic and geometric returns: The book value index (4.011), the dividends index (3.113) and the earnings index (2.829).

5.3.2 Risk Based Measures

The relatively high returns of the mid-100 stocks seem to have been harvested at higher levels of risk, measured in terms of volatility or standard deviation. Apart from the sales index, all fundamental indices of the mid-100 stocks reveal higher volatilities than the reference portfolio and the market proxy. The standard deviations of all fundamental indices are nonetheless swinging between the lower and upper boundaries of 29% except the book value index that displays a value of 31.10%. Despite generating the highest returns, the sales index, however, exhibits the lowest standard deviation of all fundamental indices with a value of 28.48%, followed by the earnings index (29.02%), the dividends index (29.41%), the SCW index (29.62%), the fundamental composite index (29.86%) and finally, the book value index (31.10%) as the most volatile fundamental index of the mid-100 stocks. In consonance with fundamental indices, the reference portfolio also boosted its performance at the expense of an additional risk

burden, showing a volatility of 29.25%.

In tandem with the increase in standard deviation, the betas of the fundamental indices of the mid-100 stocks are also higher. Despite being more diversified than their top 50 counterparts due to a greater constitution of stocks, the fundamental indices of the mid-100 stocks show both higher standard deviations and betas. The sales index reveals the lowest beta of 1.123, followed by the earnings index (1.148) and the dividends index (1.160). In spite of its mature-firm-constitution, the dividends index seems to have generated its higher returns over the earnings index at the cost of a higher standard deviation and beta. The fundamental composite index that had the second lowest beta for the fundamental indices of the top 50 stocks now comes fourth in line with a beta of 1.175. The SCW index exhibits the highest beta of 1.190 and all fundamental indices, except for the sales index and the earnings index, reveal higher betas than the reference portfolio beta of 1.157.

The maximum drawdown shows an increase from the top 50 stock figures. The SCW index of the mid-100 stocks again leads the way in terms of the maximum loss incurred during the research period, with a value of -63.98%. The reference portfolio also demonstrates a similar value of -63.96%. The sales index displays the lowest maximum drawdown (-57.26%) while the dividends index, which spearheads the fundamental indices of the top 50 stocks in terms of maximum loss incurred, is now overshadowed by the book value index. The dividends index and book value index show maximum loss values of -60.19%1 and -62.37% respectively. Although the book value displayed greater potential in growing its returns following a drop in portfolio concentration –that is, a 7.44% increase in arithmetic return - it nevertheless increases its downside risk of incurring greater maximum losses. Despite the increase in maximum loss suffered by fundamental indices and excess drawdown values over the market proxy, all fundamental indices reveal lower drawdown values than the reference portfolio.

5.3.3   Risk-Adjusted Performance

The Sharpe ratio and Treynor measure of all fundamental indices of the mid-100 stocks outperform those of both the market proxy and the reference portfolio, with the sales and fundamental composite indices again taking the lead. The sales index displays a

Sharpe ratio of 0.638 and a Treynor measure of 0.162. The fundamental composite index reveals a Sharpe ratio and Treynor measure of 0.554 and 0.141 respectively. The reference portfolio shows a Sharpe ratio of 0.279 and a Treynor measure of 0.071. The reference portfolio mildly underperforms the market proxy in terms of Sharpe ratio but outperforms with respect to its Treynor ratio. This is in symmetry with its higher standard deviation but moderate beta, relative to the market proxy. In line with its lower return and relatively high standard deviation and beta, the SCW generates the lowest Sharpe ratio and Treynor measure of all the fundamental indices, with a value of 0.309 and 0.077 respectively.

Of a more pronounced nature are the values for Jensen's alpha; contrary to the previous observation in section 5.2.3 above, all fundamental indices generate positive alphas, with the sales index revealing an alpha of 10.51% and the composite index, an alpha of 8.52%. The book value index generates an alpha of 6.73%and the dividends index produces an alpha of 4.23%. The SCW generates an alpha of 1.04%. The better results of the reference portfolio in Treynor measure terms, relative to the market proxy, translate to a positive Jensen's alpha of 0.30%.

Assuming similar levels of risk, fundamental indices outperform the reference portfolio, as highlighted by the positive information ratio demonstrated by all fundamental indices. Even the SCW index outperforms the reference portfolio but the TAIEX (market proxy) fails to even match the performance of the reference portfolio.

Under the assumption that all fundamental indices are leveraged at an annual risk-free rate of 1.3% to create a portfolio with similar volatility as the market proxy, fundamental indices outperform the market proxy by an average of 12.17% per annum as indicated by the average M-squared of the fundamental indices. Again, the sales index displays the best result for the M-squared of 0.164, followed by the fundamental composite index with an M-squared of 0.144.

Overall, the risk-adjusted returns of the fundamental indices of the mid-100 stocks show a marked improvement over their top 50 counterparts and outperform both the TAIEX market proxy and the revised cap-weighted reference portfolio.

5.4 Comparative Analysis of Top 50 and Mid-100 Indices

5.4.1 Mean-Variance-Efficiency of Fundamental Indices and Mean Reversion

Although most fundamental indices exhibit higher betas, relative to the market proxy and the reference portfolio, it would be informative to determine if the higher betas can be explained in terms of the returns generated. Cognizant of the implied linearity assumption between beta and returns, portfolios with higher betas would be justified by generating higher returns. Plotting the index beta against the arithmetic return provides important insight as to whether or not the fundamental indices are more mean-variance-efficient than the market proxy and the reference portfolio - depending on their respective positions to the security market line (SML), as well as a mean-variance-efficiency comparison between the fundamental indices of different concentrations. Figure 5.1 below displays the SML graph, drawn on the same axis, of the risk-return performance of the fundamental indices constructed from both the top 50 and mid-100 stocks.

From Figure 5.1, it can be seen that only the sales index and the fundamental composite index of the top 50 stocks generate returns that more than compensate for their slightly higher betas. Plotting above the SML is indicative of the fact that these two indices are more mean-variance-efficient, relative to the market proxy.

The other fundamental indices of the top 50 stocks, including the reference portfolio, are less optimal and can also be described as overvalued, seeing that their returns are less than commensurate to the risks inherent in the portfolio. Despite generating higher arithmetic returns than the market proxy, the fundamental indices of the top 50 stocks fail to adequately compensate for the increased risks undertaken. All fundamental indices are, nevertheless, more mean-variance-efficient than the reference portfolio. This observation is reinforced by the risk-adjusted measures discussed in sections 5.2.3 above.
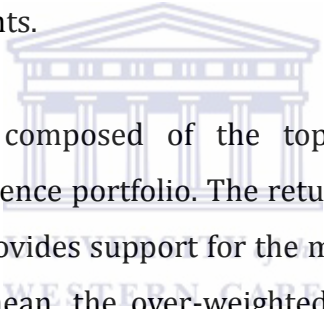
As opposed to the relative positions of the top 50 indices, most of which plotted below the SML, the mid-100 indices all plot above the SML. Despite its proximity to the SML, even the reference portfolio generates returns that more than compensate for the risks undertaken.

Figure 5.1: Security Market Line Depiction of Indices
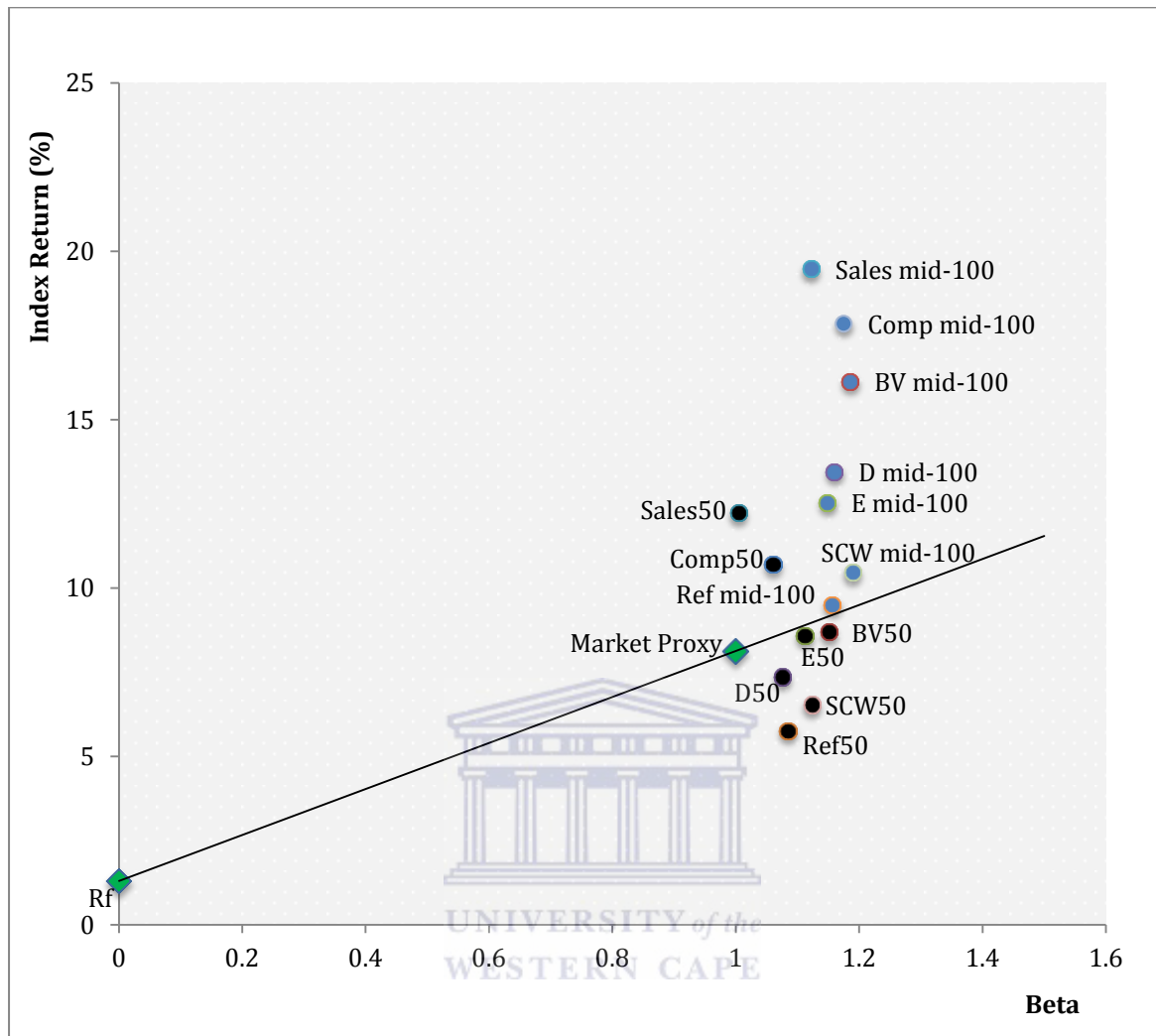
The observation from Figure 5.1 above suggests that all fundamental indices composed of the mid-100 indices (including the SCW index) are more mean-variance-efficient, as well as undervalued, relative to the market proxy, the reference portfolio and their top 50 counterparts. The sales and composite indices, which were the only mean-variance-efficient fundamental indices of the top 50 stocks, maintain their dominance with the mid-100 stocks in terms of the excess compensation offered for corresponding risk levels. The higher returns displayed by the sales index for both the top 50 and mid-100 stocks supports the argument of Arnott et al. (2005) and Hsieh (2013), where they found that sales index was superior to other indices due to the higher predictability associated with sales relative to the other fundamental variables like earnings and dividends.

The above observation brings to light the concept of mean reversion in stock prices and how the fundamental indices performed vis-à-vis the cap-weighted reference portfolio and market proxy (TAIEX). The mean-variance efficiency of fundamental indices and return drag of the cap-weighted portfolios has been partly associated with the phenomenon of mean reversion of mispriced stocks (Siegel, 2006). However, most of the fundamental indices comprised of the top 50 stocks are less mean-variance efficient than the TAIEX. The superior mean-variance efficiency of the TAIEX relative to the fundamental indices composed of the top 50 stocks does not negate evidence of mean reversion in the TAIEX stocks. The superior performance of the TAIEX is probably justified by the larger number of constituents in the TAIEX (over a thousand stocks), compared to the fundamental indices comprised of only the top 50 stocks. This explanation is made more vivid when the performance of the fundamental indices composed of the top 50 stocks is compared to their cap-weighted reference portfolio, with equal number of constituents.

All the fundamental indices composed of the top 50 stocks outperform their comparative cap-weighted reference portfolio. The return drag experienced by the cap-weighted reference portfolio provides support for the mean reversion inherent in stock prices. Post reverting to the mean, the over-weighted overvalued stocks in the cap-weighted reference portfolio creates a drag in performance relative to the fundamental indices. Even the SCW index, which is also constructed from stock price information, and is the least performer of the fundamental indices, outperforms the cap-weighted reference portfolio. The higher mean-variance efficiency of the SCW index not only supports the argument for the mean reversion in stock prices as suggested by numerous researchers (DeBondt and Thaler, 1985; Poterba and Summers, 1988; Shiller, 2005; Siegel, 2006) but also corroborates the "Shiller P/E" ratio concept. Shiller (2015) argues that, due to mean reversion in stock prices, finding a reliable estimate for a firm's P/E ratio should be based on an average of the previous 10 years of earnings, adjusted for inflation. Therefore this single 10-year-average P/E ratio captures mean earnings and a more reliable price that investors are willing to pay for the stock. The SCW index also applies the concept of averaging prices to determine a more reliable estimate of the mean price. The subsequent mean reversion of prices in the cap-weighted reference portfolio, post portfolio construction, retards the performance of the cap-weighted

reference portfolio relative to the SCW index.

When portfolio concentration is lowered and the number of constituents increased in constructing the fundamental indices, the fundamental indices composed of the mid-100 stocks exhibit a superior degree of mean-variance efficiency relative to both the TAIEX and their comparative cap-weighted reference portfolio. The increase in stock constitution for the mid-100 fundamental indices and their higher mean-variance efficiency than the TAIEX further illuminates how the mean reversion in the cap-weighted TAIEX has partly accounted in its return drag.

While advocating for the efficiency of markets, Malkiel (2003) argues that the existence of mean reversion may well be part of the dynamics of an efficient market. He argues that the mean reversion of stock prices may be consonant with interest rate movements and that mean reversion is more pronounced in some periods than others. Therefore mean reversion, he stipulates, is not necessarily a red flag for market inefficiency.

Efficient markets or not, the avoidance of cap weights, in preference for fundamental variable weights, by fundamental indexation mitigates the effect of mean reversion in its index performance and results in more mean-variance efficiency than cap-weighted portfolios.

5.4.2   Analysis of Index Concentration

Research performed on the South African equity market by Hsieh et al. (2012) did reveal that the level of portfolio concentration seldom influenced the performance of fundamental indices. This observation was attributed to the fact that, by removing the price element from the weighting of fundamental indices, the small firm anomaly is mitigated. The Taiwanese stocks, however, project relatively large levels of index concentration and also large disparities in metric weights, especially for the top 50 stocks. This probably accounts for the significant discrepancies in performance as portfolio concentration decreases.

Figure 5.2A below depicts a comparative analysis of the fundamental indices formed from the top 50 stocks and mid-100 stocks in terms of generating excess returns over

their respective reference portfolios. The purpose of this analysis is to illustrate how changes in portfolio concentration for the fundamental indices influenced performance. The graph clearly shows that the fundamental indices of the mid-100 stocks, on average, generate a higher excess return over their corresponding reference portfolio than the fundamental indices of the top 50 stocks. The mid-100 fundamental indices generate an average excess return on their reference portfolio of over 5% while the top 50 indices display an average excess return of 3.26%. In line with the superior arithmetic and geometric returns of the sales index, as discussed earlier, the sales index generates the highest excess return for both the top 50 indices and mid-100 indices of 6.47% and 9.98% respectively. The fundamental composite index is next in line with excess returns over the reference portfolio of 4.94% for the top 50 indices and 8.35% for the mid-100 indices.

Figure 5.2A: Excess Return on Reference Portfolio
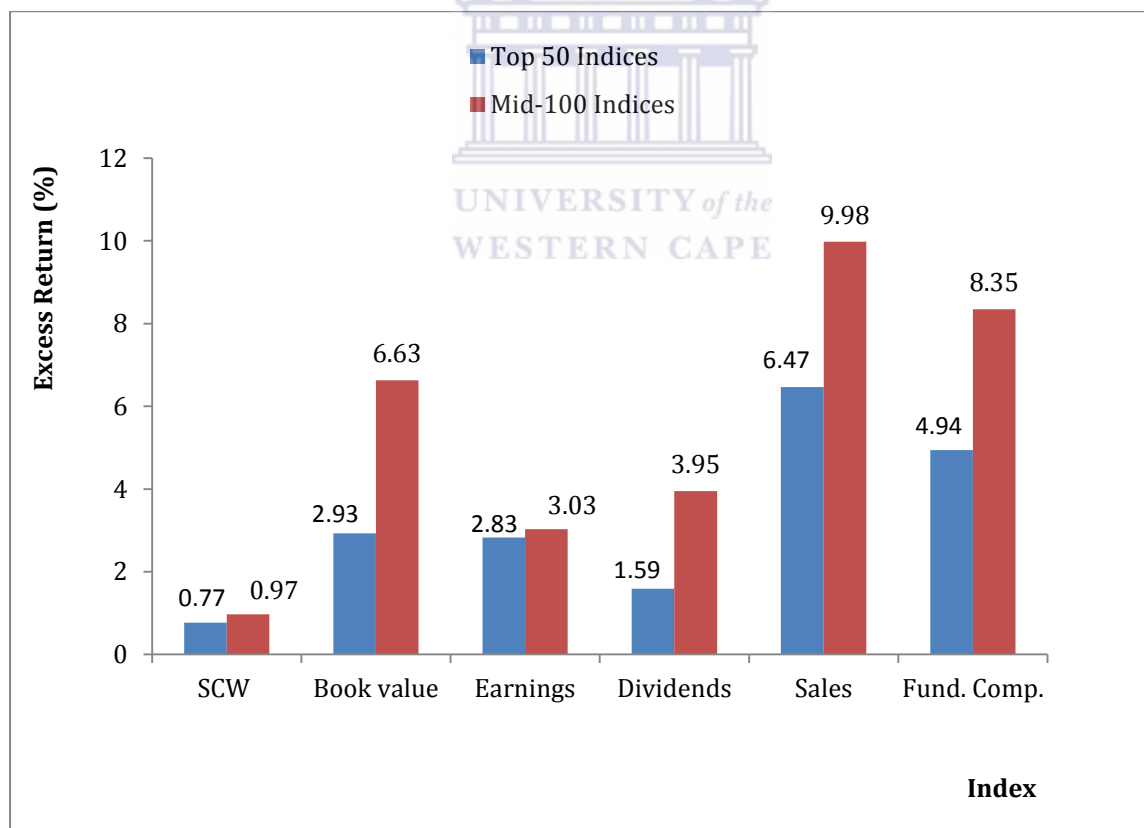
The SCW index generates the lowest excess return over its respective reference portfolios; 0.77% for the top 50 indices and 0.97% for the mid-100 indices. While the earnings index generates a higher excess return over the reference portfolio than the

dividends index for the top 50 stocks, the dividends index generates a higher excess return over the reference portfolio than the earnings index for the mid-100 stocks.

Referring back to Figure 5.1 above, the marked increase in the returns of the fundamental indices of the mid-100 stocks reinforces the argument that mid-100 fundamental indices are more mean-variance efficient following a drop in portfolio concentration. Further justification for this observation will be provided in a subsequent chapter that discusses performance attribution.

In addition to the mean-variance-efficiency and excess return analysis above, Figures 5.2B through 5.2F below provide further insight into the relative performance of the fundamental indices of different concentrations (top 50 and mid-100 indices). The figures below depict different elements of the relative risk-adjusted performance of the top 50 and mid-100 fundamental indices.

Figure 5.2B displays the comparative performance in terms of Sharpe ratios of the top 50 and mid-100 fundamental indices. All fundamental indices constructed from the mid-100 stocks reveal Sharpe ratios well above their comparative top 50 counterparts. The sales index reveals the highest Sharpe ratio for both the top 50 (0.638) and mid-100 (0.443) indices, followed by the fundamental composite index. Conversely, the SCW index displays the lowest Sharpe ratio for both the top 50 (0.189) and mid-100 (0.309) indices. Similar to the excess returns observed in 5.4.2 above, while the dividends index displays a lower Sharpe ratio than the earnings index for the top 50 indices, its Sharpe ratio for the mid-100 indices is superior to that of the earnings index.

Figure 5.2C displays the Treynor measures for the different index concentrations. The fundamental indices constructed from the mid-100 indices also display higher Treynor measures than their comparative top 50 indices, with a similar performance sequence as the Sharpe ratios for the mid-100 indices (that is, the sales index being the best performing index, followed by the fundamental composite index, book value index, dividends index, earnings index and finally the SCW index).

The Jensen's alpha, Information ratio and M-squared of Figures 5.2D, 5.2E and 5.2F respectively unveil a superior performance of the fundamental indices constructed from the mid-100 stocks over the fundamental indices comprised of the top 50 stocks. All fundamental indices of the mid-100 stocks outperform their comparative top 50 indices with respect to the Jensen's alpha, Information ratio and M-squared.

Figure 5.2B: Comparative Sharpe Ratios
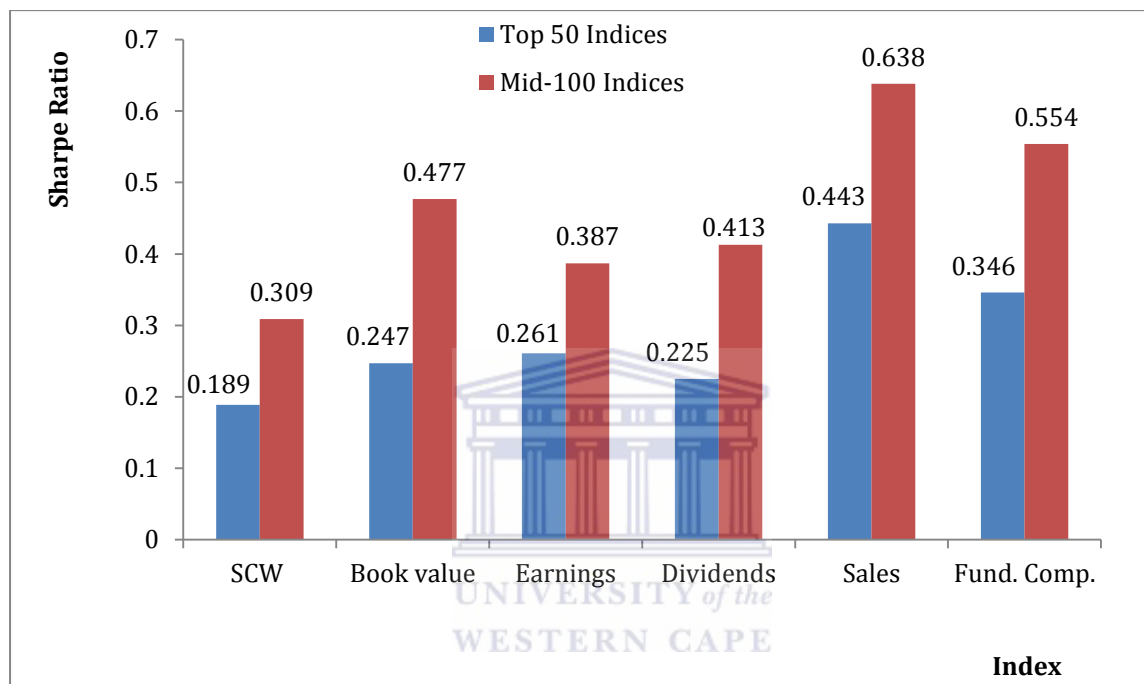
Figure 5.2D shows that while all fundamental indices composed of the mid-100 stocks generate positive alphas, only the sales index and composite index of the top 50 stocks generate positive alphas.

The graph of Information ratio in Figure 5.2E reveals that all the fundamental indices constructed from the mid-100 stocks also outperform their top 50 counterparts. However, the fundamental indices of the mid-100 stocks that are constructed from accounting metrics of size display higher Information ratios relative to their top 50 counterparts.

The SCW index, which is constructed smoothing share prices, displays Information ratios for the top 50 and mid-100 indices that are quite close and much lower than the

Information ratio of the other fundamental indices. Information ratio evaluates the performance of an index relative to the index it tracks (in this case, the reference portfolio).

Figure 5.2C: Comparative Treynor Measure
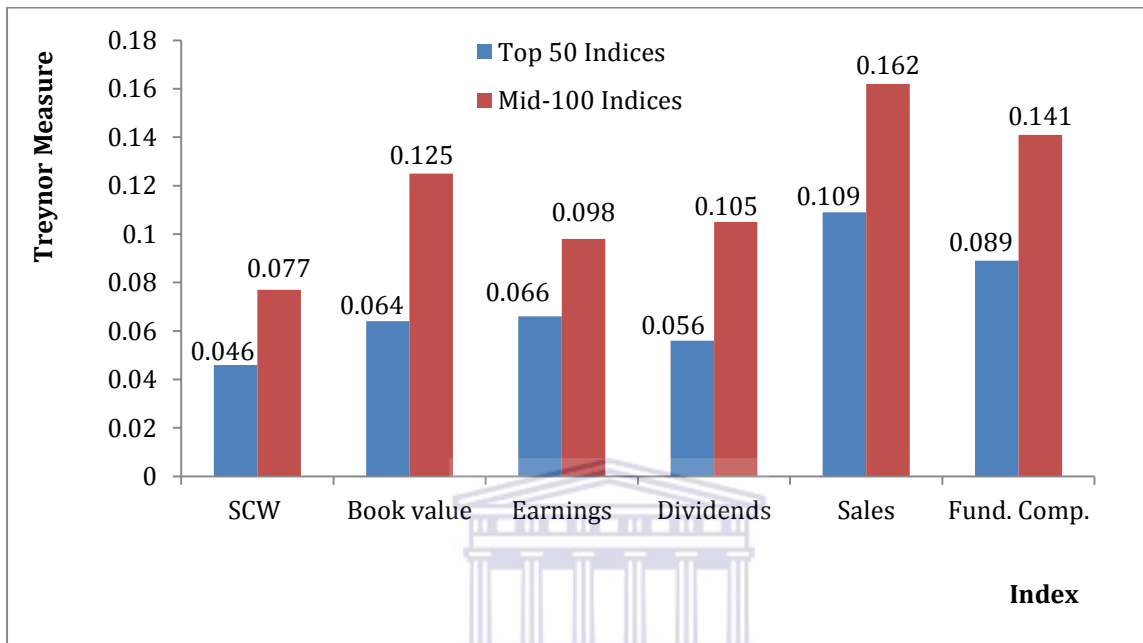
Figure 5.2D: Comparative Jensen's Alpha
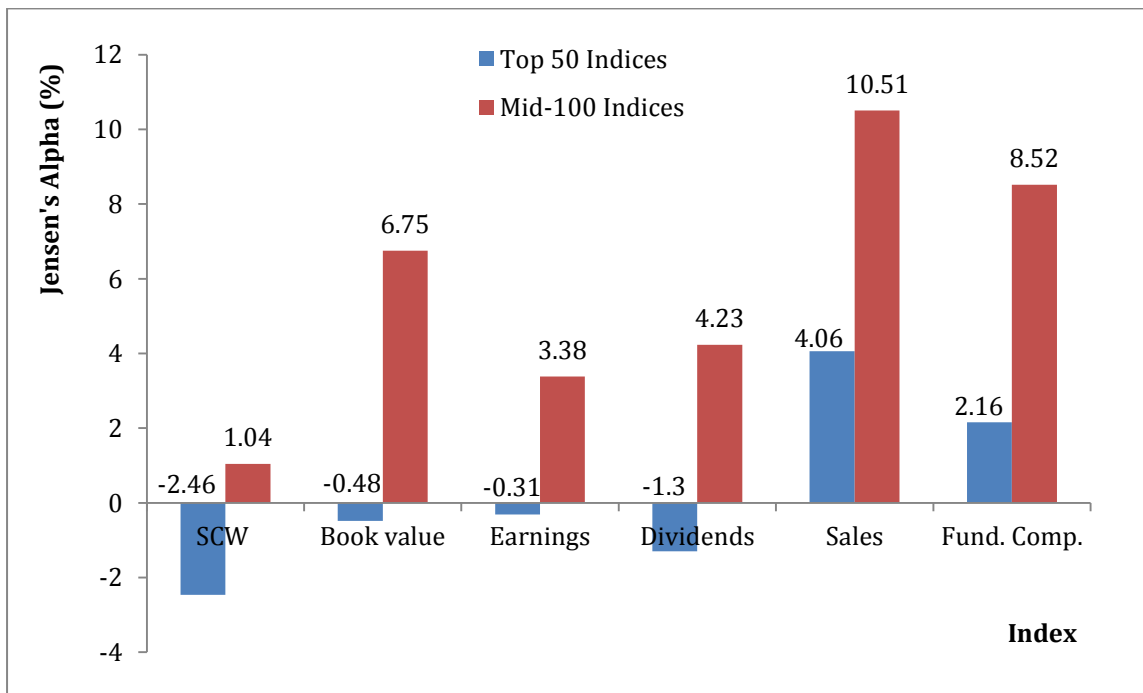
Figure 5.2E: Comparative Information Ratios
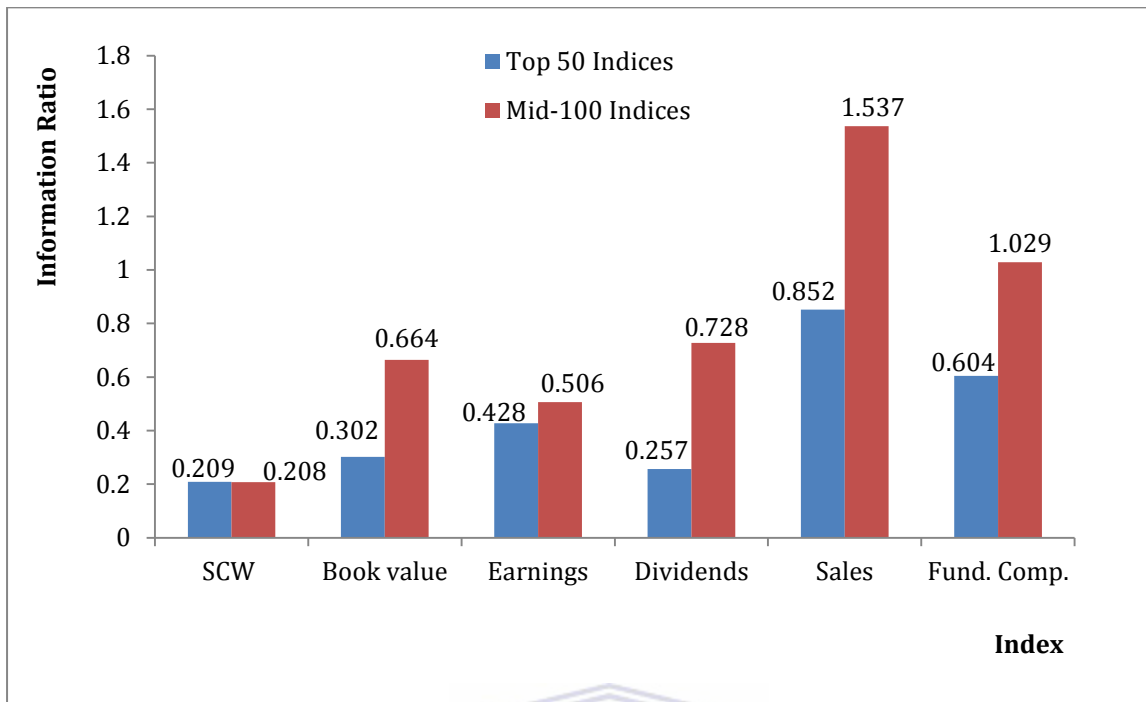
Figure 5.2F: Comparative M-Squared
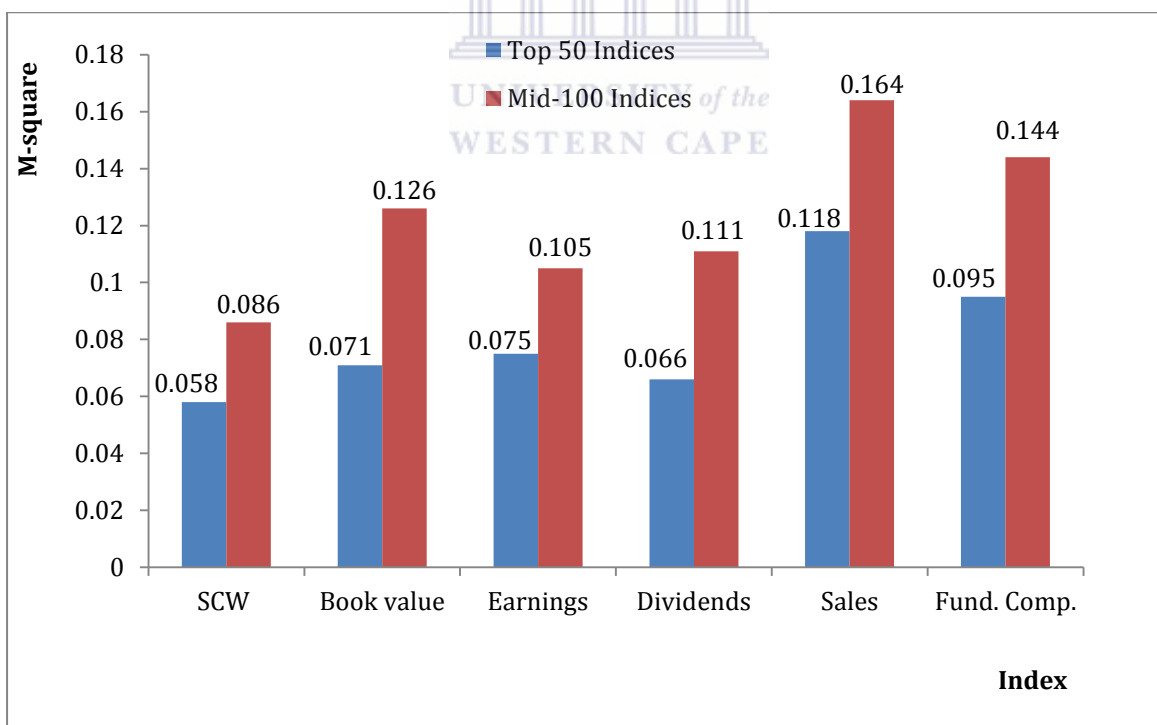
Therefore, the relative closeness of the information ratios of the SWC index of the top 50 and mid-100 indices suggests that, when leveraged at the same risk level as the reference portfolio, both the SWC index of the top 50 and mid-100 stocks reveal a

similar performance.

In sum, the level of portfolio concentration influences the performance of the fundamental indices constructed from the Taiwanese stocks. The fundamental indices constructed from the mid-100 stocks (lower level of index concentration) exhibit a much superior performance relative to their top 50 counterparts (higher level of index concentration) and their corresponding reference portfolio. This observation is out of tone with the observation of Hsieh et al. (2012).

5.5   Conclusion

The basic return, risk and risk-adjusted measures of the fundamental indices of the top 50 and mid-100 stocks were discussed in this chapter. Moreover, a comparative analysis of the performance of the top 50 and mid-100 stocks was made, in conjunction with the reference and market index.

The results show that the sales index is the best performing fundamental index for both top 50 and mid-100 stocks, generating the highest return and lowest standard deviation. Its performance is closely followed by the composite index. Although most fundamental indices of the top 50 stocks underperform the market proxy, they all outperform the reference portfolio. However, all fundamental indices of the mid-100 stocks - including the SCW index, which tailed both the market proxy and the reference portfolio of the top 50 stocks in terms of returns - outperform both the market proxy and the reference portfolio. In addition, the fundamental indices of the mid-100 stocks outperform the top 50 stocks, indicative of the fact that portfolio concentration largely influenced the performance of the fundamental indices.

Although most fundamental indices of the top 50 stocks and all the fundamental indices of the mid-100 stocks generate higher returns than the market proxy and even the reference portfolio, fundamental indices do so at the expense of greater risk burdens. Only the sales index of the top 50 stocks displays a lower standard deviation than the market. The higher standard deviations and betas of the fundamental indices of the top 50 stocks result in Sharpe ratios and Treynor measures that are lower relative to the market proxy but higher with reference to the reference portfolio. The fundamental indices of the mid-100 stocks, despite the greater risk burden relative to the market, still outperform both the market proxy and the reference portfolio on a risk-adjusted basis

Furthermore, this chapter investigated the mean-variance efficiency of the fundamental indices in terms of how the indices generate returns with respect to the required returns as determined by their betas. Their respective positions on the SML line informs the accuracy of valuation and whether superior returns where generated by optimising systematic risk. The results indicated that fundamental indices of the top 50 stocks, save the sales index and the fundamental composite index, are less mean-variance-efficient

with respect to the market proxy and the mid-100 stocks (as well as overvalued) and have generated returns, which although greater than the reference portfolio, have been inadequate with respect to the systematic risk inherent in the portfolios. The fundamental indices of the mid-100 stocks, however, are more mean-variance efficient and undervalued and generate excess returns by optimising the return-beta relation.

The mean-variance efficiency of the fundamental indices composed of the top 50 and mid-100 stocks relative to their cap-weighted reference portfolio provides some insight into the concept of mean reversion of mispriced stocks, which subsequently leads to a return drag in the return of cap-weighted portfolios.

Depicting the relative risk-adjusted performance of the indices of different concentrations reveals that fundamental indices composed of the mid-100 stocks display higher and better values for the risk-adjusted measures than their top 50 counterparts. All in all, the sales index proved to be the best performing fundamental index in all respects, followed by the fundamental composite index.
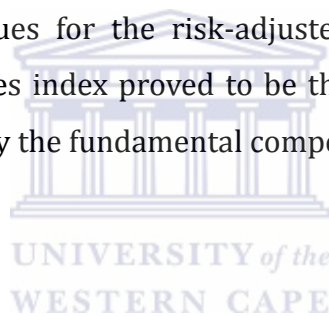
Chapter 6 : PERFORMANCE ATTRIBUTION

6.1   Introduction

In the previous chapter, the performance of fundamental indices comprised of the top 50 and mid-100 stocks was presented and discussed. A comparative analysis of fundamental indices, with the reference portfolio and the market proxy was also made. Despite the fact that most of the fundamental indices comprised of the top 50 stocks underperformed the market proxy, the mid-100 indices all outperformed both the market proxy and the reference portfolio. It was also observed that the inherent mean reversion of mispriced stocks in cap-weighted portfolios results in a return drag, propelling the mean-variance efficiency of fundamental indices. In addition to mean reversion, this chapter examines further attributes of fundamental indices that might have accounted for their superior performance over the cap-weighted reference portfolio and the market proxy.

Previous research performed on fundamental indices, as discussed in the literature review of this thesis, has made reference to fundamental indices being value or size biased because of high book-to-price or small-cap stock selection. In this chapter, a regression of the returns of all fundamental indices against the CAPM and the Fama-French (1993) 3-factor model is performed and analysed. For comparative purposes, a CAPM and Fama-French (1993) 3-factor regression of the returns of the reference portfolio is also performed. The observed results should provide insight into whether or not the observed higher returns and mean-variance efficiency of fundamental indices, especially those of the mid-100 stocks, are also propelled by the long-standing attributed investment style biases. Irrespective of the nature of the results obtained, it must be indicated that the data used in running the regressions satisfactorily meet the assumptions for the respective regressions.

6.2   Regression Results: CAPM

On the one hand, the CAPM regression aims at determining how market movements influence the performance of fundamental indices. If the excess returns of fundamental indices have a significant factor loading on the market risk premium, then their returns

are well explained by changes in the market risk premium. On the other hand, the coefficient of determination (R-squared) indicates the proportion of the return variations of the indices that are accounted for by changes in the market risk premium. The regression intercept indicates the abnormal returns that are not explained by the market risk premium at the appropriate level of significance, after accounting for possible influences on the return.

Table 6.1, split into panel A and panel B, displays the comparative results of the CAPM regression of the reference portfolio and the fundamental indices formed from the top 50 and mid-100 stocks respectively.

The results show that all fundamental indices exhibit a positive factor loading on the market risk premium. This implies that, for the fundamental indices composed of the top 50 stocks, the excess returns of all portfolios are well explained by the market risk premium, with statistically significant beta coefficients and R-squared. The high values for R-squared indicate that movements in the market risk premium satisfactorily explain the return variations of the fundamental indices, as well as the reference portfolio of the top 50 stocks.

The sales index portrays the highest R-squared (93.07%), implying that the market risk explains most of its return variations relative to the other fundamental indices of the top 50 stocks. The composite index reveals an R-squared of 85.66%. The SCW index is the next fundamental index with returns mostly explained by the market with an R-squared of 92.23%. The reference portfolio displays the highest R-squared value of all the indices investigated. This magnified R-squared for the reference portfolio (93.85%), together with the relatively high R-squared of the SCW index are logical, cognisant of the fact that these portfolios are constructed from share prices. The other fundamental indices (book value index, earnings index and dividends index) also display R-squared values of over 80%.

In order to determine if the returns of the fundamental indices generate alphas, after accounting for the proportion of the return variations explained by market risk, the sign and magnitude of the intercept and t-statistics of the fundamental indices will be

determinant in this regard.

Table 6.1: CAPM Regression Results

PANEL A: Top 50 Stocks

	Reference Portfolio	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fundamental Composite Index
R-Squared	93.85%	92.23%	83.24%	88.89%	89.89%	93.07%	85.66%
[P-value]	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Intercept	-0.002	-0.001	-0.000	-0.000	-0.001	0.003	0.002
t-statistics	-1.546	-0.481	-0.141	-0.120	-0.523	2.088	0.701
[P-value]	0.124	0.631	0.888	0.905	0.601	**0.038****	0.485
b_Market Risk Premium	1.085	1.124	1.151	1.112	1.075	1.005	1.061
t-statistics	49.573	43.065	28.282	35.897	37.838	46.513	31.007
[P-value]	**0.000*****	**0.000*****	**0.000*****	**0.000*****	**0.000*****	**0.000*****	**0.000*****

PANEL B: Mid-100 Stocks

	Reference Portfolio	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fundamental Composite Index
R-Squared	87.22%	90.66%	81.68%	87.97%	87.39%	87.24%	86.98%
[P-value]	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Intercept	0.000	0.002	0.006	0.003	0.003	0.008	0.006
t-statistics	0.084	0.979	1.641	1.104	1.328	3.330	2.557
[P-value]	0.933	0.329	0.103	0.271	0.186	**0.001*****	**0.012****
b_Market Risk Premium	1.157	1.190	1.186	1.149	1.160	1.123	1.175
t-statistics	33.146	39.297	26.791	34.305	33.409	33.173	32.800
[P-value]	**0.000*****	**0.000*****	**0.000*****	**0.000*****	**0.000*****	**0.000*****	**0.000*****

Asterisks denote percentage level of significance: *, **, *** denote 10%, 5% and 1% respectively.

Negative t-statistics signify negative alphas, whereas positive t-statistics signify positive alphas, which, however, may not be statistically significant. While both the SCW index and dividends index reveal negative intercept values of -0.001, the book value index and earnings index have intercepts of close to zero. Only the sales index and fundamental composite index have positive intercepts of 0.003 (0.3%) and 0.002 (0.2%) respectively. In support of the intercept values (alpha), the t-statistic is negative for all other indices but for the sales index and the fundamental composite index. The alpha of the sales index reveals the highest t-statistic of 2.088 while the fundamental composite index shows a t-statistic of 0.701. The dividends index reveals the lowest t-statistic for the fundamental indices of the top 50 stocks with a value of -0.523, followed by the SCW index with a t-statistic of -0.481. Having the most negative t-statistic for fundamental

indices implicitly entails having the lowest alpha (-0.1%) for the dividends index and SCW index. Overall, the reference portfolio displays both the lowest intercept and t-statistic of -0.002 and -1.546 respectively. This implies that other than the sales index and fundamental composite index, all other indices generate negative or insignificant alphas.

Albeit having a positive alpha, the t-statistic for the alpha of the fundamental composite index of the top 50 stocks is not statistically significant (P-value 0.485). Only the sales index generates a statistically significant alpha of 0.3% with t-statistics of 2.088 at a 5% significance level as indicated by its p-value of 0.038.

With respect to the mid-100 stocks, most of the fundamental indices show decreases in the proportion of the excess returns explained by the market risk, as depicted by the lower R-squared values, compared to the fundamental indices composed of the top 50 stocks.

Following the decrease in portfolio concentration, the SCW index is now the portfolio with the greater proportion of returns explained by the market as indicated by its R-squared of 90.66%. The sales index has an R-squared of 87.24%. In fact, both the dividends index and the earnings index of the mid-100 stocks display R-squared values of 87% odd. Regardless of the subtle or large differences in the R-squared values of the indices, all the fundamental indices of the mid-100 stocks nevertheless have return variations that are well explained by the market risk and reflect a high factor loading on the market risk premium. The factor loading on the market risk premium is confirmed by the high values of R-squared for the fundamental indices, indicative of the fact that market movements account for more than 85% of the return variations of most fundamental indices of the mid-100 stocks. The reference portfolio of the mid-100 stocks displays a drop in the proportion of return variations explained by the market risk as indicated by the R-squared of 87.22%. This is expected due to the fact that the composition of the reference portfolio of the mid-100 stocks is dominated by stocks with lower market capitalisation. In sum, the both the fundamental indices and the reference portfolio comprised of the mid-100 stocks show a statistically significant factor loading on the market risk premium at a 1% level of significance, as shown by

their bolded P-values of close to zero.

Having observed the drop in the proportion of return variations explained by the market in most of the fundamental indices comprised of the mid-100 stocks, all fundamental indices of the mid-100 stocks, nonetheless, reveal a positive factor loading on the market risk premium. Subsequently, fundamental indices of the mid-100 stocks have generated positive alphas as indicated by the intercept and t-statistics values. The sales index, in consonance with its performance in the top 50 stocks, generates the highest alpha of 0.8% (t-statistic of 3.330) followed by the fundamental composite index with an alpha of 0.6% (t-statistic of 2.557). The book value index, which exhibits a negligible alpha for the top 50 stocks, now displays an alpha of 0.6%, with a positive t-statistic of 1.641. The earnings index shows a t-statistics of 1.104 and the dividends index a t-statistics of 1.328 and both indices display alphas of close to 0.3%.

In spite of the positive t-statistics and alphas generated by the fundamental indices of the mid-100 stocks, only the sales index and the fundamental composite index produce statistically significant alphas at 1% and 5% levels of significance respectively; with p-values of 0.001 and 0.012 respectively. This observation is supported by their relatively large t-statistics as highlighted earlier.

6.3   Regression Results: Fama-French (1993)

Panel A and panel B of Table 6.2 display the results of the Fama-French (1993) 3-factor regression for the top 50 stocks and mid-100 stocks respectively.

6.3.1   Top 50 Indices

The results reveal that when style risk is incorporated into the performance analysis using the Fama and French (1993) 3-factor model, the fundamental indices constructed from the top 50 stocks display relatively higher R-squared values compared to the CAPM regression. While the R-squared of the SCW index for the top 50 stocks remained unchanged at 92.23% from the CAPM regression, the R-squared of the all other indices increased slightly. The R-squared of the fundamental composite index of the top 50 stocks increased to 86.31%, while sales increased to 93.13%. The book value index,

earnings index and dividends index also showed slight hikes. Even the reference portfolio revealed an R-squared increase to 94.01% and retained its potency as the portfolio with return variations most explained by market risk for the all indices constructed from the top 50 stocks. In line with performance retention, the book value index, with an R-squared of 83.58%, remained the portfolio, relative to other portfolios, with return variations least explained by movements in the market risk. All in all, the R-squared of the fundamental indices of the top 50 stocks indicate that their returns are statistically significantly well explained by the market risk premium. This deduction is confirmed by the significant loading observed in the statistical significance displayed by the p-value of the market risk premium of all fundamental indices at a 1% level of significance.

In order to determine if style risk is significant in influencing the performance of the fundamental indices of the top 50 stocks, the P-values of the factor loadings on the small cap and value premia provide insight to this investigation. Before examining the P-values, however, the factor loadings on the respective style risks are observed. Except for the SCW index, all fundamental indices comprised of the top 50 stocks display a positive factor loading on the small cap risk premium. The composite fundamental index shows the highest t-statistic of 2.751 followed by the book value index with a t-statistic of 2.067. Of the fundamental indices with a positive loading on the small cap risk premium, the earnings index displays the lowest t-statistic of 0.474 followed by the sales index with a t-statistic of 0.831. The dividends index reveals a t-statistic of 1.763. The SCW index displays a negative factor loading for small cap risk premium (t-statistic of -1.561).

Although 5 fundamental indices constructed from the top 50 stocks display a positive factor loading for small cap risk premium, only the book value index, the dividends index and the fundamental composite index of the top 50 stocks exhibit a statistically significant factor loading on the small cap risk premium. The book value index reveals a P-value of 0.04 and the dividends index reveals a P-value of 0.08, significant at a 5% and 10% level of significance respectively. The fundamental composite index reveals a P-value of 0.007, significant at a 1% level of significance. The earnings index and the sales index display P-values of 0.636 and 0.407 respectively, which are statistically

insignificant for a factor loading on the small cap risk premium at a 10%, 5% or 1% level of significance.

The reference portfolio displays a negative factor loading for small cap risk premium with a t-statistic of -2.035. With a P-value of 0.043, the reference portfolio therefore exhibits a statistically significant negative factor loading for small cap risk premium at the 5% level of significance.

With respect to value risk premium, all fundamental indices of the top 50 stocks, except the SCW index and the fundamental composite index, have a positive factor loading for value risk premium. The reference portfolio reveals the highest t-statistic of 1.890 for the value risk premium while the sales index, relative to other fundamental indices, shows the highest t-statistic of 0.720. However, neither the fundamental indices nor the reference portfolio of the top 50 stocks show any significant loading on the value risk premium, as indicated by their P-values. This implies that while size may be significant in explaining the returns of some fundamental indices, the value effect is not attributable to the performance of the fundamental indices of the top 50 stocks.

Having examined the factor loading of style risk on the fundamental indices and reference portfolio of the top 50 stocks, the regression intercepts indicate that after market risks and style influences are accounted for, only the sales index, amongst fundamental indices, generates a positive alpha of 0.3%. The sales index alpha is statistically significant at a 5% level of significance, with a t-statistic of 2.013 and P-value of 0.046. The fundamental composite index of the top 50 stocks exhibits a positive alpha of 0.4%, with a t-statistic of 1.570 and P-value of 0.119 but is not statistically significant. The earnings index and dividends index reveal alphas of close to zero, which are equally statistically insignificant.

The reference portfolio, on the other hand, exhibits a negative alpha of -0.3%, with a t-statistic of -2.107 and P-value of 0.037, which is statistically significant at a 5% level of significance. The SCW index displays a statistically insignificant negative alpha of -0.2%, with a t-statistic of -8.560 and P-value of 0.393.

Table 6.2: Fama-French 3-Factor Regression Results

PANEL A: Top 50 Stocks							
	Reference Portfolio	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fundamental Composite Index
R-Squared	94.01%	92.23%	83.58%	88.95%	90.09%	93.13%	86.31%
[P-value]	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Intercept	-0.003	-0.002	0.003	-0.000	0.000	0.003	0.004
t-statistics	-2.107	-8.560	0.831	-0.120	0.022	2.013	1.570
[P-value]	**0.037**	0.393	0.407	0.905	0.983	**0.046****	0.119
b_Market Risk Premium	1.053	1.096	1.210	1.120	1.111	1.016	1.128
t-statistics	39.086	33.971	24.078	29.060	31.650	37.863	27.070
[P-value]	**0.000****	**0.000****	**0.000****	**0.000****	**0.000****	**0.000****	**0.000****
b_SMB (Size Effect)	-0.088	-0.081	0.167	0.029	0.100	0.036	0.185
t-statistics	-2.035	-1.561	2.067	0.474	1.763	0.831	2.751
[P-value]	**0.043****	0.121	**0.040****	0.636	**0.080***	0.407	**0.007****
b_HML (Value Effect)	0.004	-0.008	0.007	0.021	0.005	0.015	-0.008
t-statistics	1.890	-0.323	0.185	0.705	0.201	0.720	-0.250
[P-value]	0.853	0.746	0.853	0.482	0.841	0.473	0.803
PANEL B: Mid-100 Stocks							
	Reference Portfolio	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fundamental Composite Index
R-Squared	87.32%	90.71%	83.66%	88.48%	87.79%	87.92%	88.16%
[P-value]	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Intercept	0.000	0.002	0.007	0.003	0.004	0.009	0.008
t-statistics	0.365	0.848	2.371	1.273	1.629	3.765	3.142
[P-value]	0.715	0.398	**0.019****	0.205	0.105	**0.000****	**0.002****
b_Market Risk Premium	1.184	1.196	1.293	1.188	1.205	1.184	1.253
t-statistics	27.313	31.754	24.796	29.093	28.277	28.855	29.415
[P-value]	**0.000****	**0.000****	**0.000****	**0.000****	**0.000****	**0.000****	**0.000****
b_SMB (Size Effect)	0.078	0.024	0.325	0.130	0.137	0.184	0.239
t-statistics	1.113	0.389	3.872	1.982	1.992	2.780	3.483
[P-value]	0.268	0.697	**0.000****	**0.049****	**0.048****	**0.006****	**0.001****
b_HML (Value Effect)	0.009	0.022	0.075	0.052	0.033	0.032	0.057
t-statistics	0.261	0.762	1.890	1.675	1.001	1.031	1.756
[P-value]	0.794	0.447	**0.061***	**0.096***	0.318	0.304	**0.081***
Asterisks denote percentage level of significance: *, **, *** denote 10%, 5% and 1% respectively.							

Although the book value index, dividends index and fundamental composite index have a statistically significant factor loading on the small cap risk premium, these indices do not generate statistically significant alphas. On the contrary, the sales index, which had no significant factor loading on the small cap risk premium, generates a statistically significant alpha. This observation lends little support to the argument that fundamental indices generate statistically significant positive alphas because of small cap risk

premium. The reference portfolio, on its part, shows a statistically significant negative factor loading on the small cap risk premium (and a statistically insignificant positive factor loading on the value risk premium) and its statistically significant alpha is explained by the market risk premium.

The absence of value bias in the fundamental indices composed of the top 50 stocks supports the argument of Hsu and Campollo (2006) that fundamental indices are different from, and outperform, value investing because fundamental indices do not necessarily underweight growth stocks but increase the weight of stocks that also grow their fundamentals.

Although revealing statistically insignificant positive factor loading for small cap and value risk premia, as discussed earlier, only the sales index, amongst the fundamental indices constructed from the top 50 stocks, generates a statistically significant positive alpha, measured by the regression intercept, after style risks are controlled for.

6.3.2   Mid-100 Indices

After portfolio concentration is lowered, the R-squared values of the fundamental indices of the mid-100 stocks, relative to their CAPM values, are also boosted. The book value index shows the highest increase in R-squared from 81.68% in the CAPM regression to 83.66% in the Fama-French (1993) regression, followed by the fundamental composite index from 86.98% to 88.16%. The SCW index displays the highest R-squared of 90.71%, which is much higher than the reference portfolio with an R-squared of 87.32%. The decrease in the R-squared of the reference portfolio is accounted for by the decrease in the market capitalisation of the stocks constituting the mid-100 reference portfolio. The sales index, which displayed the highest R-squared for the fundamental indices of the top 50 stocks, now comes in fourth place with a value of 87.13%.

In sum, the return variations of the fundamental indices of the mid-100 stocks, under the Fama-French (1993) 3-factor regression, are nevertheless well explained by market risk, as confirmed by the statistically significant P-values (0.00) of the market risk premium, at a 1% level of significance.

In analysing index performance for small cap risk premium, all fundamental indices of the mid-100 stocks, together with the reference portfolio, exhibit a positive factor loading on the small cap risk premium. In comparison with the fundamental indices of the top 50 stocks, all fundamental indices of the mid-100 stocks not only show a positive factor loading on the small cap risk premium but also display relatively higher t-statistics. The book value index displays the highest positive t-statistic of 3.872 followed by the fundamental composite index and sales index with t-statistics of 3.483 and 2.780 respectively. The dividends index and earnings index show t-statistics of 1.992 and 1.982 respectively.

Contrary to the fundamental indices of the top 50 stocks, the fundamental indices of the mid-100 stocks exhibit a statistically significant factor loading on the small cap risk premium. The higher the t-statistic of the size effect for the fundamental indices, the lower the percentage significance level at which statistical significance is observed. For instance, the book value index, the fundamental composite index and the sales index all show a statistically significant factor loading on the small cap risk premium at a 1% significance level, with relatively higher t-statistics of 3.872, 3.483 and 2.780 and P-values of 0.000, 0.001 and 0.006 respectively. So their relatively higher t-statistics result to statistical significance at a lower (1%) significance level. On the other hand, the earnings index and the dividends index, with lower t-statistics of 1.982 and 1.992 respectively, show a statistically significant factor loading on small cap risk premium at a higher (5%) level of significance.

Although exhibiting a positive factor loading on small cap risk premium, the SCW index (t-statistic of 0.389; P-value of 0.697) and the reference portfolio (t-statistic of 1.113; P-value of 0.268) - both of which are constructed from share prices - do not show any statistically significant factor loading on small cap risk premium. The results indicate that small cap risk premium is significant in explaining the returns of almost all the fundamental indexes of the mid-100 stocks. This implies that stocks with relatively smaller market capitalisation are constituents of the mid-100 fundamental indices. The presence of the small cap bias provides further explanation for the discrepancy in both the return and risk-adjusted performance of the top 50 and mid-100 indices discussed in chapter five.

All indices (both fundamental indices and the reference portfolio) constituting the mid-100 stocks exhibit a positive factor loading on the value risk premium. However, in contrast to the complete absence of a statistically significant loading on the value risk premium observed in the fundamental indices of the top 50 stocks, the returns of some of the fundamental indices of the mid-100 stocks are influenced by value risk premium statistically significantly. The relatively higher t-statistics of the book value index (1.890), the earnings index (1.675) and the fundamental composite index (1.756) indicate the positive factor loading on the value risk premium. The book value index, earnings index and the fundamental composite index display P-values of 0.061, 0.096 and 0.081 respectively. The value effect is, therefore, significant in explaining the returns of the book value index, the earnings index and the fundamental composite index comprised of mid-100 stocks at a 10% level of significance. Although the dividends index and the sales index display positive t-statistics of 1.001 and 1.031 respectively, their respective P-values of 0.318 and 0.304 are indicative of the fact that the factor loading on the value risk premium is not statistically significant.

After the style risk (size and value effect) for the fundamental indices of the mid-100 stocks are accounted for, only the book value index, the sales index and the fundamental composite index generate statistically significant abnormal returns, as indicated by the P-values of the intercept. On the one hand, the sales index generates an alpha of 0.9% (t-statistic of 3.765) and the fundamental composite index produces an alpha of 0.8% (t-statistic of 3.142); both are statistically significant at a 1% level of significance as conveyed by their P-values of 0.00 and 0.002 respectively. On the other hand, the book value index generates a positive alpha of 0.7%, with a t-statistic of 2.371 at a 5% level of significance. Although the SCW index, the earnings index and the dividends index all generate positive alphas of 0.2%, 0.3% and 0.4%, with t-statistics of 0.848, 1.273 and 1.629 respectively, their alphas are not statistically significant. This observation is substantiated by their respective P-values of 0.398, 0.205 and 0.105.

In view of the above observation of the influence of style risk on the performance of the fundamental indices composed of the mid-100 stocks, the book value index and fundamental composite index generate statistically significant alphas but their returns are also statistically significantly accounted for by known style risk (size and value

effect). The sales index also displays a statistically significant alpha but its returns are only statistically significantly accounted for by the size risk premium. Finally, the earnings index and dividends index show statistically insignificant abnormal returns but a statistically significant factor loading on the size risk premium.

Overall, the sales index is observed to generate statistically significant excess returns independent of the style influences for the top 50 stocks (where it exhibited neither size nor value effect) and statistically significant alphas with partial style risk influences for the mid-100 stocks (where only size effect was observed).This result is in line with that of Arnott et al. (2005) and Hsieh (2013), where they found that sales index was superior to other indices due to the higher predictability associated with sales relative to the other fundamental variables like earnings and dividends. The fundamental composite index also exhibits a statistically significant alpha due to its acclaimed ability to mitigate single index volatilities. The recommendation for the fundamental composite index as a more resilient index was advanced by Stotz et al. (2010), stating that the fundamental composite index mitigates the flaws of any single index. The blended nature of the fundamental composite index minimises the influence of the underperformance of any single index.
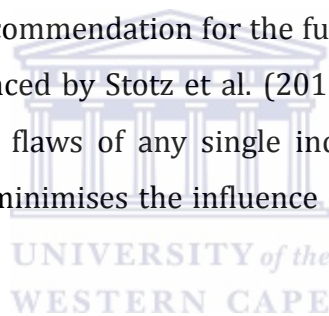
Because the regression against the Fama-French (1993) 3-factor model of the returns of the sales index of the top 50 does not reveal any statistically significant factor loading on either small cap or value risk premium, the findings suggest that most of the alpha of the sales index of the top 50 stocks must have been accounted for by other attributes, as opposed to factor-risk exposure. The two main performance attributions for the sales index composed of the top 50 stocks are:

I. Mean reversion of mispriced stocks in the cap-weighted portfolios, as discussed in the previous chapter.

II. Sales index being a superior weighting technique. This observation also lends credit to the superior and distinctive weighting technique of fundamental indexation relative to cap-weighting.

The absence of a statistically significant factor loading on the small cap bias for the earnings index and the sales index of the fundamental indices comprised of the top 50

stocks evidences the fact that these two fundamental indices also have stocks with large market capitalisation included therein. This rebuffs the argument that fundamental indices underweight large cap stocks. However, the lowering of portfolio concentration introduced the selection of stocks with lower market capitalisation for fundamental indices relative to price-sensitive indices, as a statistically significant factor loading on small cap bias is observed for all fundamental indices constructed from the mid-100 stocks; except the SCW index.

Overall, the regression results reveal that in addition to the mean reversion of mispriced stocks in cap-weighted portfolios, the superior performance of the fundamental indices of the mid-100 stocks are also partly accounted for by known style risk factors. Some of the fundamental indices of the top 50 stocks exhibit a significant factor loading on the size risk premium but show no significant factor loading on the value risk premium.

6.4 Conclusion

In order to examine what contributes (in addition to mean reversion) to the superior performance of the fundamental indices over cap-weighted indices, this chapter examined the regression results of both the CAPM and Fama-French (1993) 3-factor model. For the CAPM regression of the top 50 stocks, the reference portfolio displays the highest R-squared value of 93.85%. This signifies the fact that the return variations of the reference portfolio are better explained by market risk. Overall, all fundamental indices also display high R-squared values, with a statistically significant loading on the market risk premium.

When portfolio concentration is lowered, the CAPM regression for the mid-100 stocks reveals the SCW index (R-squared of 90.66%) as the index with return variations most explained by market movements. Like the fundamental indices of the top 50 stocks, the R-squared values of the fundamental indices of the mid-100 stocks indicate that the return variations of the mid-100 indices are also well explained by the market risk premium.

However, after accounting for the influence of market movements on the returns of fundamental indices composed of the top 50 stocks, only the sales index generates a statistically significant alpha. The fundamental composite index and the sales index of the mid-100 stocks show statistically significant alphas.

When style investing is accounted for, using the Fama-French (1993) 3-factor model, although most of the fundamental indices constructed from the top 50 stocks exhibit a positive t-statistic for small cap risk premium, only the book value index, the dividends index and the fundamental composite index show a statistically significant factor loading on the small cap risk premium. No fundamental index comprised of the top 50 stocks shows any statistically significant factor loading on the value risk premium. Sales, which showed no statistically significant factor loading on size or value, is the only fundamental index composed of the top 50 stocks that generates a statistically significant alpha, suggestive of the fact that the alpha of the sales index of the top 50 stocks is independent of the influence of style risk premium.

However, all of the fundamental indices composed of the mid-100 stocks, except the SCW index, reveal a significant factor loading on the small cap risk premium. Moreover, the book value index, earnings index and fundamental composite index also show statistically significant factor loadings on value risk premium. In addition to the sales index, the book value index and fundamental composite index of the mid-100 stocks generate statistically significant alphas after accounting for the influences of style risk. Thus, it can be concluded that both value and size effects are important in explaining the returns of the fundamental indices comprised of the mid-100 stocks.

In conclusion, upon analysing the regression results of the returns of the fundamental indices against the CAPM and Fama and French (1993) 3-factor model, the returns of all fundamental indices - irrespective of the portfolio concentration - are well explained by the market risk premium. However, only the book value index, dividends index and fundamental composite index of the top 50 stocks show a significantly positive factor loading on the small cap risk premium. Value effect does not explain the returns of the top 50 stocks with any degree of statistical significance. On the contrary, all fundamental indices comprised of the mid-100 stocks show statistically significant factor loadings on the small cap risk premium and value effect partly accounts for the returns of the book value index, the earnings index and fundamental composite index constructed from the mid-100 indices.

Chapter 7 : PERFORMANCE ROBUSTNESS

7.1   Introduction

In the previous chapter the performance attribution of the fundamental indices comprised of the top 50 stocks and mid-100 stocks were examined. The analysis of performance attribution was to determine if the superior performance of the fundamental indices was engineered by, in addition to mean reversion, the presence of value and/or size biases. However, it is also informative to investigate how robust the performance of fundamental indices have been and how their returns have been accumulated throughout the research period. Moreover, it is necessary to find out how the various indices performed in different phases of the market; mainly the bull and bear market cycles of the Taiwanese economy.

This chapter begins by discussing the tools employed in identifying the various market cycles of the Taiwanese market. Thereafter, it isolates the annual returns of the fundamental indices and examines how each index performed in different definitions of the bull and bear market cycles. Possible explanations for observed market patterns are also provided.

7.2   Identification of Market Cycles in the Taiwanese Economy

Upward and downward broad market movements within the stock market have been a frequent observation both by market participants, as well as researchers. The upward and downward movements create both stock price peaks and troughs in the stock market. Dating algorithms are often employed to identify such peaks and troughs (Maheu, McCurdy & Song, 2009). Famous amongst such dating algorithms is the one developed by Bry and Boschan (1971) to identify turning points in economic cycles. The algorithm was eventually modified by Pagan and Sossounov (2003), who used the adapted version to investigate bull and bear market cycles or economic cycles in stock markets, based on stock price movements. Therefore, in order to identify economic cycles, a determination of the peaks and troughs is first established, followed by a prescription of how long a market phase is to be observed.

Cognisant of the fact that stock market trends/cycles could outlive a year, in this research, the identification of market cycles in the Taiwanese market is done on a cyclical (annual), as opposed to a secular basis. The determination of bull or bear market cycles in the Taiwanese market is centered on price movements of the TAIEX throughout the research examination period. The price movement of the TAIEX is analysed based on its relative returns to the risk-free interest borrowing rate or as a percentage increase or decrease in the TAIEX return.

This research employs a modified version of the Lunde and Timmermann (2004) dating algorithm, whereby peaks/toughs must qualify as a bull/bear market if and only if a minimum percentage increase/decrease is attained. The 20% increase/decrease rule employed by Arnott et al. (2005) is adopted. Arnott et al. (2005) defined a bull market as a 20% increase over and above the most recent trough of the TAIEX return while a bear market is regarded as a 20% decline below the most recent peak of the TAIEX return. The steps involved in the determination of the market cycles are summarised below:

1. Note the last observed annual return – In this case, the 2001 annual return of the TAIEX (market portfolio) – and determine if it is a peak (bull) or trough (bear).

2. If "1" above is a peak, determine if the current index return has increased beyond the peak or dropped below the peak. Should it be an increase, update the current year's market cycle status with that of the previous year. Should it be a decrease, determine if the decrease is at least 20% and, if so, update the current year market cycle status to a bear market.

3. If "1" above is a trough, determine if the current index return has decreased further or increased above the trough. Should it be an increase, determine if the increase is equal to or greater than 20%. If the increase is at least 20%, then change the market cycle status to a bull market. Otherwise, retain the market cycle status of the previous year (bear market).

In accordance with the definition of a business cycle and stock market cycle by the Taiwan Council for Economic Planning and Development (CEPD), bull and bear market phases have been classified. Table 7.1 below illustrates the results of the classification.

Table 7.1: Taiwan CEPD Market Cycle Definitions

Period From	Period To	Market Cycle
2001	2007	Bull
2008	2008	Bear
2009	2010	Bull
2011	2011	Bear
2012	2014	Bull

Based on the Taiwan CEPD table above, the year 2001 in this research assumes the status of a bull market and acts as a reference point for subsequent determination of bull and bear market cycles, using the three-step process above.

As mentioned earlier, two definitions of bull and bear markets are employed: The first definition is based on the relative returns of the TAIEX (market proxy) to the risk-free rate. If the market portfolio return exceeds the risk-free rate, the market is designated a bull market. Conversely, if the market portfolio return is exceeded by the risk-free rate, the market is designated a bear market. This definition of the market cycle is denoted as "market cycle 1". The second definition, adapted from Lunde and Timmermann (2004) and Arnott et al. (2005), is based on the percentage movements of the returns of the market portfolio relative to the last peak or trough, using year 2001 (a bull market) as the kick-off year. This definition is denoted "market cycle 2".

7.3   Performance Resilience of Top 50 Stocks

In chapter 5, it was observed that apart from the dividends index and the SCW index, all fundamental indices displayed lower values for maximum drawdown relative to the market proxy and reference portfolio. On average, most fundamental indices for the top 50 stocks, however, underperform the market proxy. In order to get a better picture of the robustness of the results of fundamental indices, a year on year assessment of the relative returns of the fundamental indices against the reference portfolio and the

market proxy is undertaken; with reference to the market cycle in vogue.

Panel A and panel B of Table 7.2 below illustrate an annual analysis of the performance of fundamental indices against the reference portfolio and market proxy respectively. The values in Panel A reveal the excess returns of all indices over the reference portfolio. Panel B reflects the excess returns of all indices on the market proxy. The colour scales in the table reveal the degree of out/underperformance of the relevant comparative index. Green highlights extreme underperformance while red indicates robust outperformance. Yellow signifies negligible outperformance while the faded colours of green and red indicate average levels of underperformance and outperformance respectively. The nature of the market, under both definitions, for the relevant year is also highlighted.

Annual excess returns are obtained by finding the difference between the annual returns of each fundamental index and the reference portfolio comprised of the top 50 stocks, as well as the market proxy. Table 7.4 below, to be discussed later, displays the annual returns of the fundamental indices composed of the top-50stocks. Equations 7.1 and 7.2 below are employed in finding the excess returns on the reference portfolio and the market proxy respectively:

$$ER_{rp,\,t} = R_{i,\,t} - R_{rp,\,t} \hspace{5cm} 7.1$$

$$ER_{m,\,t} = R_{i,\,t} - R_{m,\,t} \hspace{5cm} 7.2$$

Where:
ER_{rp} is the excess return over the reference portfolio;
ER_{m} is the excess return over the market proxy;
t is the year in question;
R_{i} is the annual return of the fundamental index, i;
R_{rp} is the annual return of the reference portfolio; and
R_{m} is the return of the market proxy.

Market Cycle 1

From Panel A of Table 7.2 below, the composite index is the most resilient of all the fundamental indices, outperforming the reference portfolio in 11 out of the 14 years investigated, showing the highest outperformance in the bear market of 2002, with an excess return value of 30.86%.

In the bull market of 2009, the fundamental composite index displays its second outperformance over the reference portfolio, with a value of 20.62%; but its 2009 excess return lags behind the excess return of the dividends index (24.20%) and the sales index (22.25%). The sales index is the next most resilient index, with just one year short of the composite index's tally. That is, it outperforms the reference portfolio 10 out of 14 years, with its highest excess return of 28.20% generated in 2002. On average, fundamental indices outperform the reference portfolio in 2 of the 3 bear markets and in 9 of the 11 bull markets of market cycle 1.

The SCW index is the least robust of the fundamental indices against the reference portfolio in bear markets. The SCW index underperforms the reference portfolio in 1 of the 3 bear markets under market cycle 1 but in 6 of the 8 bear markets under market cycle 2. The SCW index also underperforms the reference portfolio in 6 of the 11 bull markets under market cycle 1.

Table 7.2, Panel B, also presents similar results in terms of year-on-year excess returns of the fundamental indices of the top 50 stocks over the market proxy. Market cycle 1 and market cycle 2 both display bear markets in 2002, 2008 and 2011. All fundamental indices of the top 50 stocks outperform the market proxy in the bear market of 2002. This is also observed against the reference portfolio in panel A above. In 2008, all fundamental indices of the top 50 stocks outperform the reference portfolio and the market proxy, save for the dividends index that lags behind the reference portfolio, underperforming the reference portfolio by -1.33%. The dividends index also underperforms the market proxy by -1.55%. However, all fundamental indices underperform the market proxy in the bear market of 2011.

Table 7.2: Excess Returns of Top 50 Indices

PANEL A: Excess Return Over Reference Portfolio									
Year	Market cycle 1	Market cycle 2	Market proxy	Risk Free Rate	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	[7]Fund. Comp. Index
2001	Bull	Bull	-2.55	-28.03	16.42	3.32	13.21	2.67	-8.73	2.41
2002	Bear	Bear	4.81	24.6	2.99	26.99	14.73	11.88	28.20	30.86
2003	Bull	Bull	11.12	-23.98	1.59	5.47	1.01	-0.55	14.91	7.02
2004	Bull	Bear	8.78	4.03	-1.04	4.07	0.62	-2.84	15.79	5.98
2005	Bull	Bear	9.90	3.43	-3.22	-1.43	0.78	1.17	8.91	3.49
2006	Bull	Bear	1.28	-17.7	-3.1	-2.86	8.49	1.48	1.59	0.45
2007	Bull	Bear	2.9	-5.58	-2.28	-0.46	2.06	7.48	15.05	3.23
2008	Bear	Bear	-0.94	44.23	0.83	0.35	1.67	-2.49	1.33	1.9
2009	Bull	Bull	10.13	-74.43	5.37	13.36	13.61	24.20	22.25	20.62
2010	Bull	Bear	0.21	-10.67	-2.81	0.82	-4.41	-3.22	3.13	0.55
2011	Bear	Bear	-0.43	20.23	-0.31	-8.68	-2.66	-0.73	-3.64	-6.66
2012	Bull	Bull	-2.36	-11.78	0.84	2.23	-0.09	4.25	1.79	-1.1
2013	Bull	Bull	-3.86	-15.18	-1.66	4.86	-4.37	-6.85	-7.63	7.13
2014	Bull	Bull	-7.43	-26.07	2.83	-7.83	-3.71	-11.53	-2.05	-8.32

PANEL B: Excess Return Over Market Proxy									
Year	Market cycle 1	Market cycle 2	Reference Portfolio	Risk Free rate	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fund. Comp. Index
2001	Bull	Bull	2.55	-25.48	18.97	5.87	15.76	5.22	-6.18	4.97
2002	Bear	Bear	-4.81	19.79	-1.82	22.18	9.92	7.07	23.39	26.05
2003	Bull	Bull	-11.12	-35.1	-9.52	-5.64	-10.11	-11.67	3.79	-4.1
2004	Bull	Bear	-8.78	-4.75	-9.82	-4.71	-8.16	-11.62	7.01	-2.8
2005	Bull	Bear	-9.9	-6.47	-13.12	-11.33	-9.13	-8.73	-0.99	-6.41
2006	Bull	Bear	-1.28	-18.98	-4.39	-4.15	7.21	0.19	0.31	-0.84
2007	Bull	Bear	-2.9	-8.48	-5.18	-3.36	-0.84	4.58	12.14	0.32
2008	Bear	Bear	0.94	45.18	1.77	1.29	2.61	-1.55	2.28	2.84
2009	Bull	Bull	-10.13	-84.56	-4.76	3.23	3.48	14.07	12.12	10.49
2010	Bull	Bear	-0.21	-10.87	-3.02	0.61	-4.62	-3.43	2.92	0.35
2011	Bear	Bear	0.43	20.66	0.12	-8.26	-2.23	-0.3	-3.22	-6.23
2012	Bull	Bull	2.36	-9.42	3.2	4.59	2.27	6.61	4.15	1.26
2013	Bull	Bull	3.86	-11.32	2.2	8.72	-0.51	-2.99	-3.77	10.99
2014	Bull	Bull	7.43	-18.64	10.26	-0.39	3.72	-4.1	5.39	-0.89

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[7] The expression "Fund. Comp. Index" denotes the Fundamental Composite Index.

So of the 3 bear markets of "market cycle 1", fundamental indices outperform the market proxy in 2 of the 3 bear markets and on average, outperform the market proxy in 6 of the 11 bull market cycles.

The fundamental composite index, which, on average return basis, underperforms the sales index, however tends to be more robust, as it outperforms in 11 of the 14 years This observation is in line with the recommendation of Stotz et al. (2010) that the composite index mitigates the flaws of any single fundamental index and can, therefore, be expected to be more resilient in generating performance.

Market Cycle 2

Under market cycle 2, there are 6 bull markets corresponding to 2001, 2003, 2009, 2012, 2013 and 2014 and 8 bear markets. Of the 8 bear markets, the SCW index appears to be the least robust of all the fundamental indices, seeing that it underperforms both the market proxy and the reference portfolio in 6 of the 8 bear markets, with the worst performance in the bear market of 2005 (That is, -3.22% and -13.12% against the reference portfolio and market proxy respectively). Irrespective of the fact that the dividends index generates the highest annual returns in 2009 and 2012 (as shown in Table 7.4 below), the dividends index is the least robust of fundamental indices constructed out of accounting metrics of size. In all, it underperforms the reference portfolio in 7 of the 14 years and the market proxy in 8 of the 14 years. Moreover, of the 8 bear markets cycles, the dividends index underperforms the reference portfolio in 5 bear market cycles and underperforms the market proxy in 6 bear market cycles. The sales index and the fundamental composite index underperform the reference portfolio in only 1 bear market proxy(2011) and underperform the market proxy in only 2 of the 8 bear markets cycles (2005 and 2011). Therefore the sales index and fundamental composite index **outperform** the reference portfolio in 7 of the 8 bear markets and the market proxy in 6 of the 8 bear market cycles.

However, the book value index, earnings index and dividends index underperform the reference portfolio in 4, 3 and 4 of the 8 bear market cycles respectively. Overall, fundamental indices outperform the reference portfolio in 6 of the 8 bear market cycles and in 4 of the 6 bull markets of market cycle 2. The fundamental indices constructed

from the top 50 stocks, however, exhibit lower resilience than the market proxy in bear markets under market cycle 2. On average, fundamental indices outperform the market proxy in only 3 of the 8 bear markets but outperform the market proxy in 5 of the 6 bull markets.

The robustness of some of the fundamental indices of the top 50 stocks (the SCW index and the earnings index) is relatively lower than that of the market proxy and the reference portfolio, especially in bearish environments. However, other fundamental indices, especially the fundamental composite index and the sales index display superior robustness in both bull and bear markets. It is, nonetheless, surprising that both elite indices of fundamental indices (the sales index and the composite index) underperform the reference portfolio in the bull market of 2014.

This could be attributable to the fact that only the first six months of the returns of 2014 are considered, as data was only available up until June 2014 at the time of the research.

7.4   Performance Resilience of Mid-100 Stocks

Still under the dual definition application of market cycles, the performance of the mid-100 stocks are analysed to determine their relative levels of robustness against the market proxy and the reference portfolio.

Equations 7.1 and 7.2 above are also employed in determining the excess returns of the fundamental indices, constructed from the mid-100 stocks, over the reference portfolio and the market proxy respectively. Panel A of Table 7.3 below outlines the excess returns of the fundamental indices over the reference portfolio while Panel B displays the excess returns over the market proxy. The year-on-year analysis of the excess returns of the fundamental indices over the reference portfolio and market proxy is based on the dual interpretation of market cycles (market cycle 1 and market cycle 2).

Market Cycle 1

On average return basis, fundamental indices of the mid-100 stocks display higher excess returns over the reference portfolio and market proxy after portfolio concentration is reduced.

Table 7.3: Excess Returns of Mid-100 Indices

PANEL A: Excess Return Over Reference Portfolio									
Year	Market cycle 1	Market cycle 2	Market proxy	Risk Free Rate	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fund. Comp. Index
2001	Bull	Bull	-18.02	-43.50	0.56	-19.62	-13.34	-9.07	5.69	-2.28
2002	Bear	Bear	-10.59	9.2	4.24	41.46	29.58	18.76	34.72	36.71
2003	Bull	Bull	14.39	-20.71	13.54	28.87	12.1	15.92	17.4	23.09
2004	Bull	Bear	9.56	4.81	1.65	9.95	-0.02	-7.11	12.31	15.55
2005	Bull	Bear	-1.61	-8.08	-2.85	-11.48	-7.18	-5.87	1.5	-8.27
2006	Bull	Bear	-5.58	-24.56	-2.65	19.39	-2.71	6.72	8.48	7.32
2007	Bull	Bear	3.81	-4.67	-4.83	-0.62	1.71	10.38	3.66	1.98
2008	Bear	Bear	1.38	46.56	-4.24	-1.36	-0.94	-1.48	3.66	0.09
2009	Bull	Bull	-28.32	-112.9	7.48	3.27	8.23	22.97	32.71	17.48
2010	Bull	Bear	4.45	-6.42	9.48	18.51	11.25	6.73	11.23	15.64
2011	Bear	Bear	8.37	29.02	2.25	4.19	6.14	8.01	8.5	5.36
2012	Bull	Bull	-4.36	-13.77	3.4	3.22	5.48	2.85	-0.41	3.09
2013	Bull	Bull	-12.39	-23.71	-6.15	-3.15	-8.72	-4.9	1.24	0.07
2014	Bull	Bull	5.35	-13.28	-2.97	3.92	-2.37	-2.13	6.56	8.19
PANEL B: Excess Return Over Market Proxy									
Year	Market cycle 1	Market cycle 2	Reference Portfolio	Risk Free Rate	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fund. Comp. Index
2001	Bull	Bull	18.02	-25.48	18.58	-1.6	4.68	8.94	23.71	15.74
2002	Bear	Bear	10.59	19.79	14.84	52.05	40.17	29.36	45.32	47.31
2003	Bull	Bull	-14.39	-35.1	-0.85	14.49	-2.29	1.53	3.01	8.71
2004	Bull	Bear	-9.56	-4.75	-7.9	0.39	-9.57	-16.66	2.75	6
2005	Bull	Bear	1.61	-6.47	-1.24	-9.87	-5.57	-4.26	3.11	-6.67
2006	Bull	Bear	5.58	-18.98	2.93	24.97	2.87	12.31	14.06	12.9
2007	Bull	Bear	-3.81	-8.48	-8.64	-4.43	-2.1	6.57	-0.15	-1.83
2008	Bear	Bear	-1.38	45.18	-5.62	-2.74	-2.32	-2.86	2.28	-1.29
2009	Bull	Bull	28.32	-84.56	35.79	31.58	36.54	51.28	61.03	45.8
2010	Bull	Bear	-4.45	-10.87	5.03	14.06	6.8	2.28	6.78	11.19
2011	Bear	Bear	-8.37	20.66	-6.12	-4.18	-2.23	-0.36	0.13	-3.01
2012	Bull	Bull	4.36	-9.42	7.76	7.58	9.84	7.2	3.94	7.45
2013	Bull	Bull	12.39	-11.32	6.23	9.23	3.67	7.49	13.63	12.46
2014	Bull	Bull	-5.35	-18.64	-8.32	-1.44	-7.73	-7.48	1.2	2.84

For example, looking at 2002, the book value index and dividends index boosted their excess return over the reference portfolio from 26.99% and 11.88% for the top 50

stocks to 41.46% and 29.58% respectively for the mid-100 stocks. The earnings index, sales index and the fundamental composite index also reveal hikes in excess returns generated over both the reference portfolio and market proxy. However the performance of the fundamental composite index of the mid-100 stocks has been a tad worse-off in the 2008 bear market of market cycle 1 against the market proxy.

The fundamental composite index, which previously outperformed both the market proxy and the reference portfolios in 2008, now underperforms the market proxy in 2008 by -1.29%. The fundamental composite index, nonetheless, maintains its superior returns over the reference portfolio in other bull and bear markets.

The SCW index, the book value index and the dividends index also underperform the market proxy in 2008, as well as in bear market of 2011. The sales index overshadows the fundamental composite index in terms of performance robustness. Although the sales index underperforms the reference portfolio in the bull market of 2012 (-0.41%) and also underperforms the market proxy in the bull market of 2007 (-0.15%), it, nevertheless, outperforms both the reference portfolio and the market proxy in all 3 bear markets of market cycle 1.
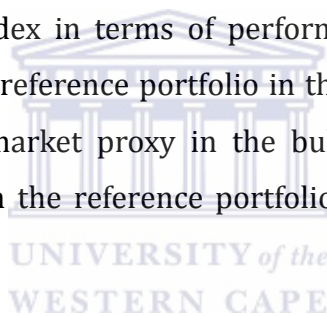
Overall, fundamental indices comprised of the mid-100 stocks outperform the reference portfolio and market proxy in 8 of the 14 years considered, and also in 2 of the 3 bear markets of market cycle 1 (as observed in the top 50 indices) but with much larger excess returns in the periods where outperformance is observed. With respect to the bull markets of market cycle 1, fundamental indices, on average outperform the reference portfolio and market proxy in 7 of the 11 bull markets.

Market Cycle 2
In terms of market cycle 2, the SCW index, book value index, dividends index and earnings index underperform the reference portfolio in 3 of the 8 bear market environments. This represents a general improvement on the performance of the top 50 stocks, which, on average, underperformed the reference portfolio in 4 bear markets. Under market cycle 2, both the sales index and the fundamental composite index underperform the reference portfolio in only a single bear market. However, the

fundamental composite index underperforms the market proxy in 4 of the 8 bear markets while the sales index underperforms the market proxy in only 1 bear market, reinforcing the inherited resilience of the sales index for the mid-100 stocks.

The book value index produces the highest excess return of 41.46% over the reference portfolio in 2002 while the sales index generates the highest excess return of 61.03% over the market proxy in 2009. The SCW index and the earnings index display the least robust performance against the market proxy as they underperform the market proxy in 5 out of 8 bear markets, which, despite still being less resilient than the market proxy, have seen an improvement from the top 50 indices.

Although the performance of some fundamental indices (such as the fundamental composite index) might have slightly waned in certain bear markets following the decrease in portfolio concentration, other individual fundamental indices of the mid-100 stocks appear to have been more resilient in both bullish and bearish market conditions relative to the market proxy and reference portfolio.

Under market cycle 2, fundamental indices outperform the reference portfolio in 6 of the 8 bear markets but outperform the market proxy in only 3 of the 8 bear markets. With respect to the bull markets, fundamental indices of the mid-100 stocks outperform the reference portfolio in 4 of the 6 bull markets and outperform the market proxy in 5 of the 6 bull markets.

The SCW index displayed the worst resilience with respect to the market proxy for both the top 50 and mid-100 indices and, despite attempts to smooth it of share price volatilities, the SCW index has not been completely shielded from the vagaries of share prices.

7.5   Illustration of Annual Returns

7.5.1   Top 50 Indices

Table 7.4: Annual Percentage Index Returns For Top 50 Indices

	Market Proxy	Risk Free Rate	Reference Portfolio	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fundamental Composite Index
2001	29.17	3.69	31.72	48.13	35.04	44.93	34.39	22.99	34.13
2002	-17.77	2.03	-22.58	-19.58	4.42	-7.85	-10.70	5.62	8.29
2003	36.15	1.05	25.03	26.62	30.50	26.04	24.48	39.94	32.05
2004	5.74	0.99	-3.04	-4.07	1.03	-2.42	-5.88	12.75	2.95
2005	7.74	1.27	-2.16	-5.38	-3.59	-1.39	-0.99	6.75	1.33
2006	20.52	1.54	19.24	16.13	16.37	27.73	20.71	20.83	19.68
2007	10.38	1.90	7.48	5.20	7.02	9.54	14.96	22.53	10.71
2008	-43.25	1.92	-42.31	-41.49	-41.96	-40.64	-44.80	-40.98	-40.41
2009	84.80	0.24	74.66	80.04	88.02	88.27	98.86	96.91	95.29
2010	11.25	0.38	11.04	8.24	11.86	6.63	7.82	14.17	11.60
2011	-19.95	0.70	-19.52	-19.84	-28.21	-22.18	-20.25	-23.17	-26.18
2012	10.21	0.79	12.57	13.40	14.79	12.48	16.82	14.35	11.47
2013	12.01	0.69	15.87	14.21	20.73	11.51	9.02	8.24	23.00
2014	19.25	0.61	26.68	29.51	18.85	22.97	15.15	24.63	18.36

Table 7.4 above displays the annualised returns of the fundamental indices for the top 50 stocks from 2001 to mid-2014, as well as the corresponding returns of the risk-free interest rate, the market proxy and the reference portfolio.

In 2001, all indices of the top 50 stocks generated positive annual returns, with the SCW index generating the highest return of 48.13% followed by the earnings index revealing an annual return of 44.93%. The sales index, which so far has displayed lofty results, generates the lowest return of 22.99%. In 2002, there is a massive drop in returns for all indices – most of them showing negative returns – except for the book value index, the sales index and fundamental composite index that generate positive returns.

Although the sales index generated the lowest return in 2001, its overall superior arithmetic return performance ensues from the highest returns generated in 5 of the 14 years investigated (2003, 2004, 2005, 2007 and 2010). Although generating higher

returns in 5 (listed above) of the 14 years examined, the sales index generates its highest return of 96.91% in 2009; lagging behind the dividends index with an annual return of 98.86%. The fundamental composite index closely follows the sales index in terms of annual returns and even generates the highest return in 2002 (8.29%) and 2013 (23.00%). Irrespective of its highest return generated in 2001, the SWC index's mediocre performance, relative to other fundamental indices, was engineered by the huge loss in 2002 (-19.58%) and feebler returns of subsequent years.

7.5.2 Mid-100 stocks

Table 7.5 below presents the year-on-year performance of the mid-100 stocks. Although the market cycles of the top 50 stocks is rhetorical in the mid-100 stocks, there are, however, more frequent observations of higher returns generated by the mid-100 stocks and a relay of annual return outperformance is highlighted. For instance, in 2001, the sales index of the mid-100 stocks robs the SCW index of its highest return stance observed in the top 50 stocks, and generates a return of 52.87%.

Table 7.5: Annual Percentage Index Return For Mid-100 Indices

	Market Proxy	Risk Free Rate	Reference Portfolio	SCW	Book Value Index	Earnings Index	Dividends Index	Sales Index	Fundamental Composite Index
2001	29.17	3.69	47.18	47.74	27.57	33.85	38.11	52.87	44.90
2002	-17.77	2.03	-7.17	-2.93	34.29	22.41	11.59	27.55	29.54
2003	36.15	1.05	21.76	35.30	50.63	33.86	37.68	39.16	44.85
2004	5.74	0.99	-3.82	-2.16	6.13	-3.83	-10.92	8.49	11.74
2005	7.74	1.27	9.35	6.50	-2.13	2.17	3.48	10.85	1.08
2006	20.52	1.54	26.10	23.45	45.49	23.39	32.83	34.58	33.42
2007	10.38	1.90	6.57	1.74	5.95	8.28	16.96	10.24	8.55
2008	-43.25	1.92	-44.63	-48.87	-45.99	-45.57	-46.12	-40.97	-44.54
2009	84.80	0.24	113.11	120.59	116.38	121.34	136.08	145.82	130.60
2010	11.25	0.38	6.80	16.28	25.31	18.05	13.53	18.03	22.44
2011	-19.95	0.70	-28.32	-26.08	-24.13	-22.18	-20.31	-19.82	-22.96
2012	10.21	0.79	14.57	17.96	17.79	20.04	17.41	14.15	17.66
2013	12.01	0.69	24.40	18.25	21.25	15.68	19.50	25.64	24.47
2014	19.25	0.61	13.89	10.92	17.81	11.52	11.77	20.45	22.08

What is more, in 2002, the fundamental composite index relinquishes its superior return position observed in the top 50 stocks to the book value index of the mid-100 stocks, which generates a return of 34.29%. In addition, the earnings index and dividends index of the mid-100 stocks join the ranks of the book value index, sales index and the fundamental composite index in generating positive annual returns in 2002. The improved average returns of the SCW index of the mid-100 stocks is partly attributed to the minimised losses of 2002 of only -2.93% relative to the -19.58% seen in the top 50 stocks.

In addition to generating highest returns in 6 of the 14 years, as opposed to 5 of the 14 years for the top 50 stocks, the sales index generates higher return differentials compared to other indices, which provided the backbone for its relative superior average returns. In 2009, all fundamental indices, as well as the reference portfolio, generate returns in excess of 100%. In 2008 and 2011, all indices, except the risk free rate generate large negative returns, with the SCW index generating the highest loss of -48.87% in 2008 and -26.08% in 2011.
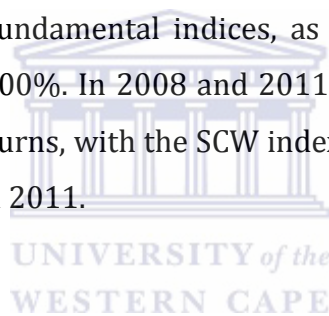
7.6   Investigation of Return Patterns

The annual percentage index returns tables (7.4 and 7.5) show huge losses made by both fundamental indices and the market proxy in 2008 and 2011. While the losses of 2011 might have taken the market aback, the losses of 2008 are far from surprising. Although the dissolution of the Lehman brothers in September 2008 and the subsequent sub-prime crisis might have taken roots from the U.S. stock market woes, its effect on other world economies was hardly delayed. Taiwan, like most export-led Asian economies, was greatly affected owing to Taiwan's overly reliance on the exportation of hi-tech products. The high correlation between the Taiwanese market and the U.S. Dow Jones Industrial average (DJIA) and the fact that the U.S. has been a long-standing trading partner with Taiwan implies that economic belches in the U.S. are rapidly transmitted over to Taiwan. Post the economic tsunami of 2008, a study by Hsu and Moroz (2009) revealed that shocks in U.S. markets are more than proportionately felt by Taiwan but the Taiwanese economy fails to adequately capitalise on the bullish spheres

of the U.S. market. The findings of Hsu and Moroz (2009) were evidenced in how the economic shocks in the U.S. market rippled through the Taiwanese market and the world at large.

7.7 Conclusion

This chapter examined how the fundamental indices performed in terms of performance robustness against the market proxy and reference portfolios in different market environments. Market environment was defined in terms of bull and bear market phases with two different definitions applied in interpreting the market phases. The return patterns were also briefly discussed.

In analysing the robustness of the fundamental indices of the top 50 stocks, the sales index generates higher returns in 5 of the 14 years investigated, but comes second to the fundamental composite index in terms of robustness of performance in bull and bear market cycles. The fundamental composite index and the dividends index each generate highest returns in 2 of the 14 years but in terms of resilience in market cycles, the dividends index is the least robust index after the SCW index. On average, however, fundamental indices of the top 50 stocks outperform the reference portfolio in 8 of the 14 years investigated. Fundamental indices also outperform the market proxy and reference portfolio in 2 of the 3 bear markets of market cycle 1. Under market cycle 2, fundamental indices of the top 50 stocks outperform the reference portfolio in 6 of the 8 bear markets and outperform the reference portfolio in only 3 of the 8 bear markets. Fundamental indices of the top 50 stocks show sturdy resilience in bull markets, greater resilience against the reference portfolio and mild resilience against the market proxy.

The fundamental indices of the mid-100 stocks show higher annual returns than the top 50 indices. The sales index becomes the most resilient fundamental index, following its increase in the number of years in which it generated highest returns (6 out of 14) and the drop in the resilience of the fundamental composite index in 2008. Fundamental indices of the mid-100 stocks, on average, reflect a similar resilience with the top 50 stocks against the reference portfolio but much stronger resilience against the market proxy. The fundamental indices of the mid-100 stocks also generate higher excess returns over the market proxy and reference portfolio. Some fundamental indices have, however, failed to match the robustness of the market proxy in bear environments but the sales and the composite indices have prevailed in both bear and bull phases of the market.

Chapter 8 : CONCLUSION

8.1   Summary of Study

The EMH and the law of one price provide a platform for both MPT and asset pricing models that assume investor rationality. The CAPM and APT are built around investor rationality and efficient markets, assuming a linear relationship between returns and the systematic risk inherent in the asset. These models evolve from the work of Harry Markowitz (1952). The APT model, however, relaxes some of the tenuous assumptions of the CAPM but both models, nonetheless, provide a reference point against which investors can make asset allocation decisions.

The empirical observation of deviations of asset prices from the predictions of the CAPM and other models founded on the EMH have resulted in the introduction of the term capital market anomalies. These anomalies imply that, the implementation of certain investment strategies could generate risk-adjusted returns in excess of what is justified by the CAPM. Such anomalies include the size effect, value effect, contrarian strategies and January effect. In an attempt to explain these anomalies, researchers have advanced reasons such as "bad model" problems (methodological tweaking) and hidden risk factors that are not captured by the CAPM. Some researchers have attributed the observation altogether to being random. In order to account for the alleged hidden risk elements, Fama and French (1993) develop a 3-factor model, which in addition to the market risk premium, also captures the small cap and value risk premia. Carhart (1997) further extends the model of Fama and French (1993) to capture the risk inherent in the momentum anomaly.

Whilst expected utility (EU) theory provides the framework for asset pricing models that advocate investor rationality, prospects theory of Kahneman and Tversky (1979) accounts for aspects of human behaviour, which may not necessarily lead to rationality, as predicted by EU theory. Prospects theory of Kahneman and Tversky (1979) describes how investors frame decisions based on other cognitive factors other than just the mean return and variance of the asset being considered. Prospects theory employs an S-shaped value function to illustrate how the subjective utility of investors is influenced by their perception of loss or gain, judged against a reference point. Building on the work of

Kahneman and Tversky (1979), other researchers have documented other behavioural biases such as herd behaviour, heuristic simplification, segregation, combination and cancellation, all in an effort to further explain the cognitive aspects that drive investors' trading behaviour.

In the presence of investor overreaction and irrational investor behaviour, markets become less efficient and the market portfolio ceases to be mean-variance efficient. Motivated by the return drag inherent in the market portfolio as a result of capitalisation weighting that potentially over-weights overvalued stocks and under-weights undervalued stocks, Arnott et al. (2005) introduced the concept of fundamental indexation whereby assets are weighted not by their market capitalisation but by the value of their fundamental metrics of size. Support for the concept was later provided Siegel (2006) in his article, "the noisy market hypothesis". The noisy market hypothesis states that markets are prone to unpredictable temporary shocks, which prevent assets from reflecting their intrinsic values. The chasm between the intrinsic value of the asset and the market price is described as noise. Moreover, Siegel (2006), alongside other researchers, stipulate that stock prices have a tendency of reverting to their mean (intrinsic) value. Hence, the subsequent mean reversion of prices creates a return drag in cap-weighted portfolios. Arnott et al. (2005) argue that by employing price-insensitive metrics of size to weight assets for investment portfolios, the potential return drag associated with cap-weighting (in the presence of noisy markets) could be mitigated. It is the mean reversion of stock prices that precipitates the superior performance of fundamental indexation.

Despite garnering support the world over, with a myriad of evidence to corroborate the superiority of the concept, fundamental indexation has yet been rebuffed by researchers like Perold (2007), Kaplan (2008) and Blitz and Swinkels (2008). These researchers have criticised both the rationale of the noisy market hypothesis and mathematical logic on which the concept rests. Other researchers have attributed the observed performance of fundamental indexation to known priced risk factors, such as value effect, observed in a vast volume of empirical literature.

Arnott and Shepherd (2009) stipulate that, not only does fundamental indexation outperform cap-weighted portfolios but that fundamental indexation has an even greater potential to outperform in emerging markets due to more articulate mispricing inherent in the prices of emerging market stocks. However, research on fundamental indexation performed on the Taiwanese stock market by Lobe and Walkshäusl (2008) revealed that the fundamental composite index constructed using price-insensitive metrics of size for the Taiwanese stocks underperformed the cap-weighted index. Recent developments in the Taiwanese market, which have triggered a downgrade of the market to emerging market status, coupled with the potential of fundamental indices to generate higher risk-adjusted returns over cap-weighted portfolios in emerging markets - as suggested by Arnott and Shepherd (2009) - provide the motivation for this research study.

The research period runs from January 2001 to June 2014 and the TEJ database is employed as the source of data. In order to answer the research questions of this study, fundamental indices of different concentrations and corresponding cap-weighted portfolios are constructed. Fundamental indices are constructed for the top 50 and mid-100 stocks weighted by the constituents' book value, earnings, dividends and sales. Fundamental cap-weighted indices are also constructed for the different portfolio concentrations. The rationale for using the top 50 and mid-100 stocks was to align this research study with other indices on the Taiwanese market. The cap-weighted reference portfolios for the top 50 and mid-100 stocks, weighted by market capitalisation, are also constructed to allow for a more equitable comparison with the fundamental indices. The TAIEX is employed as the market index and the yield on the 3-month Taiwanese Treasury bill is used as the risk-free interest rate. This research study also taps into the methodology applied by Chen, Chen and Bassett (2007) for estimating fundamental values of assets. Chen, Chen and Bassett (2007) propose the use of smoothed cap weights (SCW); by finding the median share prices over a predetermined window period, as a more suitable estimate of the intrinsic value of an asset. SCW indices for the top 50 and mid-100 indices are also constructed.

To provide more perspective on the research questions posed in chapter four of this thesis, the contextual interpretation of the research questions are restated below, as

well as the empirical results.

Q1: Mean-variance efficiency of fundamental indices relative to cap-weighted portfolios and mean reversion.

The results indicate that for the fundamental indices constructed from the top 50 stocks, all fundamental indices constructed from accounting variables, with the exception of the dividends index outperform the market proxy (TAIEX) in terms of arithmetic returns. In terms of geometric returns, all fundamental indices outperform the TAIEX. However, all fundamental indices, but the sales index, display higher total risk (standard deviation) than the TAIEX. All fundamental indices also display higher systematic risk (beta coefficients) than the TAIEX. Because of the higher measures of risk displayed by most of the fundamental indices, all fundamental indices, except the sales index and fundamental composite index underperform the TAIEX in terms of risk –adjusted measures and are therefore less mean-variance efficient than the TAIEX.

Judging the performance of fundamental indices constructed from accounting variables against the cap-weighted reference portfolio, which is a more appropriate benchmark, reveals that all fundamental indices outperform the cap-weighted reference portfolio in terms of higher returns, lower risks and higher risk-adjusted returns. Therefore, although most fundamental indices constructed from the top 50 stocks are less mean-variance efficient than the TAIEX, all fundamental indices of the top 50 stocks are nevertheless more mean-variance efficient than their comparative cap-weighted reference portfolio. The dividends index is the worst performer of the fundamental indices constructed from the top 50 stocks, based on accounting variables, while the sales index is the best performer.

When portfolio concentration is reduced, all fundamental indices constructed from the mid-100 stocks outperform both the TAIEX and their corresponding cap-weighted reference portfolio in terms of mean returns. Although all fundamental indices of the mid-100 stocks yet display higher risk measures than the TAIEX, fundamental indices of the mid-100 stocks are more mean-variance efficient than the TAIEX as indicated by their higher risk-adjusted measures. Only the dividend index and book value index of the mid-100 stocks display higher standard deviations than their corresponding cap-

weighted reference portfolio. All fundamental indices of the mid-100 stocks are, nonetheless, more mean-variance efficient than the cap-weighted reference portfolio. The mean-variance efficiency of the fundamental indices constructed from the mid-100 stocks also portray the presence of mean reversion of stock prices, thereby providing support for Siegel's (2006) work. Because overvalued stocks were more than proportionately included in the cap-weighted portfolios, their subsequent mean reversal generates lower returns, resulting in the lower returns and lower risk-adjusted returns of the TAIEX and cap-weighted reference portfolio.

The fundamental indices of the mid-100 stocks are also more mean-variance efficient that their top 50 counterparts. The lower mean-variance efficiency of most of the fundamental indices composed of the top 50 stocks does not rebuff the presence of mean reversion in mispriced cap-weighted stocks included in the top 50 stocks. The mean-variance inefficiency of the fundamental indices constructed from the top 50 stocks against the TAIEX and mid-100 indices can be attributed to the lower diversification inherent in the top 50 stocks relative to the other two portfolios. The underperformance of the top 50 indices relative to the mid-100 indices is also suggestive of more pronounced mispricing inherent in large cap stocks.

Q2: Relative performance of Smoothed Cap Weights (SCW).
The SCW index constructed from the top 50 stocks displays the lowest performance of all the fundamental indices and underperforms the TAIEX, generating lower average returns and higher risk measures. The SCW index is, however, superior to its comparative cap-weighted reference portfolio. Therefore, the SCW index of the top 50 stocks is more mean-variance efficient than the cap-weighted reference portfolio but less so relative to the TAIEX. Despite smoothing cap weights to mitigate stock price volatility, as suggested by Chen, Chen and Bassett (2007), the SCW index of the top 50 stocks, like the dividend index, underperform the TAIEX. When portfolio concentration is lowered, the SCW index of the mid-100 stocks displays a greater ability to dispel of stock price volatility through price smoothing and generates higher risk-adjusted returns than both the TAIEX and the cap-weighted reference portfolio. The underperformance of the SCW index of the top 50 stocks is attributable to the generally lower risk-adjusted returns of most of the fundamental indices constructed from the top

50 stocks rather than to the absence of stock price volatility screening. The higher mean-variance efficiency of the SCW of the mid-100 stocks over the cap-weighted reference portfolio and the market proxy indicates that smoothing cap weights has a greater potential to reflect a fairer value of stock prices; more so in less concentrated portfolios (the mid-100 index).

Q3: Performance attribution of fundamental indices.

Upon regressing the returns of the fundamental indices (SCW inclusive) against the CAPM and Fama- French (1993) 3-factor model, all fundamental indices, as well as cap-weighted, display a significant factor loading on the market risk premium. This is reflected in their relatively higher R-squared. This implies that the return variations of the fundamental indices of both the top 50 and mid-100 stocks are well explained by changes in the market risk premium. Post observing a statistically significant loading on the market risk premium for the CAPM regression by the fundamental indices, only the sales index of the fundamental indices of the top 50 stocks generates a statistically significant alpha. For the mid-100 indices, the fundamental composite index joins the sales index in generating a statistically significant alpha.

To determine if style risks (size and value) significantly influence the returns of fundamental indices, the Fama-French (1993) 3-factor regression for the top 50 indices indicates that except for the SCW index, all fundamental indices comprised of the top 50 stocks display a positive factor loading on the small cap risk premium. However, only the book value index, the dividends index and the fundamental composite index of the top 50 stocks exhibit a statistically significant factor loading for small cap risk premium. No fundamental index of the top 50 stocks displays a statistically significant factor loading on the value risk premium. More importantly, the sales index, which displays no statistically significant factor loading on the small cap risk premium or value risk premium, is the only fundamental index to generate a statistically significant alpha of 0.3% at a 5% level of significance.

With respect to the fundamental indices of the mid-100 stocks, all fundamental indices, except the SCW index, show a statistically significant positive factor loading on the small cap risk premium. The decrease in the size of the stocks forming the mid-100 indices

introduces a small cap bias in all the fundamental indices of the mid-100 stocks. The book value index, earnings index and fundamental composite index also display a statistically significant positive factor loading on the value premium. However, only the sales index and fundamental composite index generate statistically significant alphas of 0.9% and 0.8%, at a 1% and 5% levels of significance respectively.

In response to the research problem, the returns of some of the fundamental indices of the top 50 stocks are partly accounted for by size effect but not value risk premium. In addition, the sales index of the top 50 stocks is the only fundamental index that generates statistically significant alphas that is independent of the influence of style risk premia. The returns of the fundamental indices of the mid-100 stocks are statistically significantly influenced by size effect. The mid-100 indices also display returns which are partly accounted for by value risk premium. Despite being influenced by style risk premia, the sales index and fundamental composite index of the mid-100 stocks still generate statistically significant alphas.

Q4: Performance robustness of fundamental indices.

To determine how robust the fundamental indices were with respect to the TAIEX and cap-weighted reference portfolio, two interpretations of market cycles were evoked: Market cycle 1 (based on the annual return differentials between the TAIEX and the risk-free rate) and market cycle 2 (based on the whether the TAIEX return dropped or increased by more than 20% from the previous high or previous low). For the top 50 stocks, the fundamental composite index displays the highest resilience, outperforming the TAIEX and reference portfolio in 11 of the 14 years. The sales index comes next, outperforming the TAIEX and reference portfolio in 10 of the 14 years. On average fundamental indices outperform the TAIEX and reference portfolio in 2 of the 3 bear markets and in 6 of the 11 bull markets of market cycle 1.

Under market cycle 2, fundamental indices, on average, outperform the cap-weighted reference portfolio in 6 of the 8 bear markets and in 4 of the 6 bull markets. Fundamental indices of the top 50 stocks show lower resilience against the market proxy; only outperforming in 3 of the 8 bear markets but in 5 of the 6 bull markets. However, of the 8 bear markets, the fundamental composite index and sales index

outperform the TAIEX and the reference portfolio in 6 and 7 bear markets respectively. For the mid-100 indices, the sales index assumes the position of the fundamental composite index as the most resilient index, outperforming the TAIEX and reference portfolio in all 3 bear markets of market cycle 1. On average, the fundamental indices of the mid-100 stocks show a similar level of resilience as the top 50 indices against the TAIEX and the reference portfolio, in both market cycle 1 and market cycle 2, but with higher excess returns generated. The SCW index was the least resilient of all the fundamental indices for both the top 50 and mid-100 indices. The lower resilience of the SCW index is probably accounted for by the price element in the size metric used in constructing this index. All in all, the fundamental composite index and the sales index for both the top 50 and mid-100 stocks display the most resilience against the TAIEX and reference portfolio. This supports the argument of Arnott et al. (2005) that fundamental indices show higher resilience than the cap-weighted reference portfolio in bear markets and (at least) a similar level of resilience in bull markets.

8.2 Implications of the Study

The results of this research study have the following implications for the Taiwanese market:

- Fundamental indices of the mid-100 stocks are more mean-variance efficient than all cap-weighted indices (TAIEX and reference portfolio), indicative of the presence of mean reversion in stock prices, as posited by Siegel (2006).

- Fundamental indices of the top-50 stocks, save for the sales and fundamental composite index, are less mean-variance efficient than the TAIEX.

- The lower mean-variance efficiency of the fundamental indices of the top 50 stocks relative to the TAIEX is attributable to the lower diversification inherent in the top 50 indices relative to the market proxy.

- Smoothing cap weights have potential to mitigate stock price volatility in stocks and generate excess risk-adjusted returns, but more so for portfolios with lower concentration and higher diversification.

- The returns of the fundamental indices of the top 50 stocks are partly accounted for by small cap risk premium and no value risk premium while the returns of the mid-100 stocks are accounted for by size risk premium and party by value risk

premium. However, the sales index generates statistically significant alphas independent of the influence of style risks.

- On average, fundamental indices show a higher resilience than the cap-weighted reference portfolio. All in all, the sales index and the fundamental composite index are the best performing fundamental indices in terms of mean-variance efficiency, robustness and generation of alphas post accounting for known style risk premia. The results of the study also suggest that the recent developments in the Taiwanese equity market, triggering a downgrade to emerging market status, have probably rendered this market more susceptible to benefit from the perks of fundamental indexation.

8.3 Limitations of this Study and Recommendations for Further Research

One of the main limitations of this study is the absence of an investigation of the momentum factor in investigating the return variations of fundamental indices. Regressing the returns of the fundamental indices against the Carhart (1997) 4-factor model would shed some light as to the influence of momentum effect on the returns of fundamental indices. Therefore, future studies on fundamental indexation on the Taiwanese equity market should consider such an investigation.

Another limitation is the lack of an out of sample test performed in analysing the results to provide more robustness to the findings. The absence of this test is partly accounted for by the misgivings in the reliability of previous year's data. With the unraveling of future years of data, subsequent research on this market should consider performing such a test.

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