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Evidence from the FTSE 100 Index 1984 – 2004

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Abstract

Capitalisation weighting has added 8,000 basis points of incremental returns to the FTSE 100 Index compared to an equally weighted portfolio of the same constituents. Industry factors explained 66% of the incremental returns, while size and style factors explained 2%. Firms that ranked in the top ten by market capitalisation had above average risk adjusted returns. The capitalisation weighted index volatility was lower than the equally weighted counterpart during tail events in the return distribution. Diversification benefits have arisen because the biggest firms either had above average returns or below average covariance, compared to the rest of the portfolio constituents.

1 . Introduction

Markowitz (1952) famously demonstrated that portfolio risk depends more upon the average covariance between the returns of portfolio constituents than upon the average risk of portfolio constituents. Furthermore, if the expected returns and risk of constituents are equal, investors will prefer to concentrate more of their portfolio assets into securities whose returns have the lower covariance with each other and with the portfolio returns as a whole. Unfortunately, as with expected returns, the covariances between securities and industry groups are temporarily variable. Authors such as Malevergne and Sornette (2002) point out that portfolio optimisation based on normal covariance patterns between the universe of portfolio constituents is complicated by the tendency for correlations between the returns of all assets to increase during times of market panic. Malevergne and Sornette (2002) suggest that portfolio optimisation based upon the expected covariances between security returns during extreme (tail) events, rather than normal events, will lead to more efficient portfolio diversification.[1] However, such optimisations may be difficult to implement, if the findings of Elton and Gruber (1973) and Elton et al. (1978) still apply, namely that superior information concerning future covariances may be as difficult to acquire as superior information concerning returns. Indeed DeMiguel et al. (2005) find little difference between the efficiency of simple diversification strategies and a variety of ex-post optimised portfolios, and point out the danger of ex-ante optimisations based on unstable parameter forecasts, or parameter forecasts made with wide confidence intervals.

Given the apparent difficulty in forecasting the covariance between the returns of different firms and asset classes, it is reassuring that Evans and Archer (1968) and subsequent studies demonstrate that considerable diversification benefits (risk reduction) can be achieved by adopting a naïve strategy of simply dividing assets equally between the stocks of a randomly selected sample of firms. Such a naïve strategy requires considerably less forecasting and computational effort than the mean variance optimisation methods suggested by Markowitz (1952) or Malevergne and Sornette (2002).

The problem with a naïve diversification strategy is that it will not be as efficient at maximising return or minimising risk as more sophisticated approaches based on modern portfolio theory (MPT) if investors do have some ability to forecast returns and covariances.

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[1] Portfolio diversification is a means by which investors can either increase their portfolios' expected returns without a commensurate increase in the expected volatility of those returns, or alternatively decrease their portfolios' expected volatility without a commensurate decrease in expected returns, while the theoretical mean variance efficient portfolio is a portfolio in which this process has been taken to its optimum limit according to the principles of modern portfolio theory.

According to proponents of the efficient markets hypothesis, the weights of constituents in the so called "market equilibrium portfolio" must be the optimal weights of the mean variance efficient portfolio. If this were not the case, it would imply that smart investors could consistently earn a market beating risk adjusted return by holding portfolios that differed in their construction to that of the market. Furthermore, apart from minor inefficiencies due to technical factors such as variations in the method of free float adjustment between different indexes, the constituent weights of equity market proxy portfolio benchmarks, such as the Russell 3,000 or the FTSE Allshare, should also approximate those of the mean variance efficient portfolio. It may also be argued that, from a practical perspective, the constituent weights of a sub-index such as the FTSE 100 should be closer to the mean variance efficient market portfolio for that constituent universe than an equally weighted portfolio that can only benefit from naive diversification.[2]

In fact most supporters of the efficient market hypothesis and researchers such as Dimson et al (2002 p. 39) appear to believe that capitalisation weighted indexes, ideally adjusted for free float, are the most suitable benchmarks for measuring the performance of an aggregate market or sector. Notwithstanding this, many professional investors, financial journalists and authors such as Arnott et al. (2005) or Hirschey (2001), express concern that in recent years capitalisation weighted indexes, such as the FTSE 100 and NASDAQ Composite, have become too dominated by a few very large firms or industry sectors. In fact, they suggest that the distribution of firm weights is so heavily skewed towards the largest firms that the

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[2] Of course, the problems of benchmark error identified by studies such as Roll (1977) and Roll (1978) causes most if not all market index portfolios to deviate from the true market portfolio in the strictest CAPM sense, although it might be argued that an imperfect proxy is better than no proxy.

naive diversification benefits arising from having a large number of constituent firms in the portfolio are lost. The concern seems to arise from the idea that in a very concentrated index, or market, the idiosyncratic risk of the largest firms contributes excessively to the systematic risk of the capitalisation weighed index or market portfolio. However, if markets are efficient and capitalisation weights are equilibrium weights, this is not an issue from a theoretical viewpoint, even in the most concentrated of markets. Nonetheless, the Financial Times (2000b) reports that Merrill Lynch Investment Management created an equally weighted version of the FTSE 100 as a benchmark because it "should show lower volatility, thanks to better diversification." Further comment on "the weighting game" is provided by the Financial Times (2000a).

The information presented in Table 1 shows that the largest five constituent firms by market capitalisation accounted for 40% of the total value of the FTSE 100 Index portfolio on the 3rd of August 2005. In fact, at that time, the FTSE 100 Index accounted for 80% of the value of the 2,500 or so UK firms listed on the London Stock Exchange.[3] Thus, passive investors in the FTSE 100 Index, or active funds benchmarked to it would aim to have 40% of their portfolio invested in the stocks of just five firms, while investors aiming to track the whole equity market would have 32% of their portfolio invested in just five firms, i.e. 40% $\times$ 80% = 32%. Dimson et al (2002 pp 28-33) report that the UK market is the 7th least concentrated among the 17 countries in their study. The UK market concentration has also been higher than at present during the early part of the twentieth century. However, Dimson et al also point out that concentration in the UK equity market reached a 101 year low in 1995 before rising very rapidly to present levels that are about 20% above the 101 year average.

[3] London Stock Exchange data file for 30th June 2005

Superficially, the bias in many markets towards large firms appears to run counter to the naïve diversification principles of Evans and Archer (1968), with respect to passive capitalisation weighted stock index portfolios of the UK market. However, high levels of concentration are consistent with the mean variance optimisation principles of Markowitz (1952), if the largest firms have expected returns that are sufficiently high or their covariance with the rest of the (market proxy) portfolio is sufficiently low to justify their increased weight in a (market proxy) portfolio. In fact, four unrelated sectors are represented by the top five firms listed in Table 1, while the correlations between the daily returns of the five firms are low enough to indicate that substantial diversification benefits can be obtained by just holding the four or five largest firms listed on the UK market. At an international level, Dimson et al (2002 p. 118) report that an equally weighted global equity market portfolio had a higher standard deviation than a capitalisation weighted global equity portfolio over the 101 year duration of their study.

The debate over weights is important given that stock indexes serve as model portfolios for passive investors and as benchmarks for measuring the performance of active investors. A recent working paper by Haberle and Ranaldo (2005) argues that many so called passive indexes actually have more in common with actively managed portfolios. The fundamental weighting scheme proposed by Arnott et al (2005) would seem to be an extreme example of an actively managed portfolio being proposed as a benchmark index. While actively managed portfolios are fine if they can produce adequate risk adjusted returns for their investors, confusion is likely to arise if they are presented as passive portfolios, or used as benchmarks against which the performance of other actively managed portfolios are measured. Given the findings of (Roll 1977, Roll 1978 and Bailey 1992) confusion and ambiguity should be avoided, if at all possible, when creating benchmarks.

Unfortunately, the theoretical mean variance efficient portfolio remains a hypothetical construct that cannot be created ex ante due to the lack of perfect knowledge about the future covariances and return distributions of the portfolio constituent universe. Likewise, an ex post recreation based on the realised statistical behaviour of constituent securities may be of limited value because it is unlikely to generalise well to changing conditions in the future. However, simple comparisons of the risk reward characteristics of the capitalisation weighted portfolios of real investors with those of a hypothetical equally weighted portfolio is of potentially greater value. This is because we can gain understanding of how effective investors in the real world are, on average, at optimising portfolio weights in relation to the naive diversification of an equally weighted benchmark of the same constituents. If it is agued that the diversification of a market capitalisation weighted index of a major stock market must reflect the structure of the average investor in that market, or section of the market represented by the index,[4] a recreation and study of a market index portfolio provides an opportunity to evaluate the average level of success achieved by investors in creating diversified portfolios.

In order to evaluate the contribution of capitalisation weights to the variance and returns of the FTSE 100 Index, this paper presents a simple method for decomposing the variance covariance matrix (VCM) of portfolio returns into sub-components of the average variance

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[4] Bear in mind that by definition, a properly constructed value weighted composite index of a particular investment universe represents the average portfolio composition of all investors, active and passive, whose investment activities are restricted to the securities available in that particular universe. Hence, the market portfolio by definition represents the average portfolio composition of all investors. Therefore, it follows that the characteristics of a properly constructed stock market index are the characteristics of the average investors' portfolio in that particular market.

and average covariance. It then examines the contribution of capitalisation weights to portfolio returns as well as to subcomponents of the variance covariance matrix, i.e. total volatility as reflected by average covariance and average variance, using the FTSE 100 Index portfolio as an example. The incremental returns arising as a result of capitalisation weights were regressed upon a size factor, a style factor and industry factors derived from the total returns of the ten “New Economic Groups” that make up the FTSE All Share Index.

2 . Derivation of data sample

This study uses data over the period January 1984 through December 2004 from the UK FTSE 100 Index. The following discussion details the processes used to recreate the FTSE 100 Index over the period using historic constituent lists supplied by FTSE International together with prices and market values from Thomson Financial Datastream in order to decompose the historic VCM of constituent returns over the life of the index to date.

In a time series study of the contribution of capitalisation weights to the structure of the variance covariance matrix of portfolio returns such as this, it is necessary to identify the names of constituent firms and their weights as well as their returns throughout the life of the index (portfolio). Therefore, the choice of index is limited by the availability of data identifying not only current constituents but historic index constituents and the original base constituents. These conditions are necessary in order to allow re-creation of the historic index portfolio enabling the historic VCM to be studied, using financial databases such as Thomson Financial Datastream. As a value weighted index of the 100 largest firms listed on the London Stock Exchange the FTSE 100 Index meets all of the above criteria. It has a history from inception in January 1984 through to the present, while the original constituent list together with the names and dates of subsequent additions and deletions is publicly available. In addition, the constituent selection procedures and calculation methods appear to be more transparent than those of competing index providers. Furthermore, the contribution of the largest firms to the total value of the FTSE 100 Index increased, and by some measures doubled, over the last ten years. These characteristics combined with the depth and liquidity of the constituents, and size of the London Stock Exchange as a whole, justify the selection of the FTSE 100 for this study. In fact in a study of the 100 largest UK market constituents prior to the formation of the FTSE 100 Index in January1984, Dimson and Marsh (1984) concluded that the tracking error of the FTSE 100 Index in relation to the UK market portfolio was likely to small in economic terms. The residual tracking error that they did find arose primarily as a result of the absence of small firm exposure in the FTSE 100 Index and to a lesser extent as a result of sector imbalances.

Daily dividend adjusted price series for all FTSE 100 Index constituents past and present were used to calculate the daily dividend-inclusive simple percentage returns for the FTSE 100 Index constituents. These were used to decompose the variance covariance matrix of FTSE 100 Index portfolio returns. However, logarithmic equally weighted and value weighted FTSE 100 Index returns were used for time series analysis and for converting daily returns to monthly returns.[5]

2.1. Incremental variance and incremental standard deviation

The value weighted and equally weighted monthly variance (*VWV* and *EWV*, respectively) are estimated by taking the sum of the squared daily value and equally weighted returns over

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[5] It is standard practice to use logarithmic returns for time series econometric analysis and simple returns for aggregating individual constituent returns series into a portfolio return, further details are provided by authors such as Campbell et al. (1997).

twenty trading days. The square root of *VWV* and *EWV* serve as estimates of the realised value and equally weighted monthly realised standard deviations *VWSD* and *EWSD*, respectively. The incremental monthly standard deviation (*ISD*) is derived by subtracting the *EWSD* from the *VWSD*. The *ISD* represents the contribution to portfolio volatility that is directly attributable to the capitalisation weights of portfolio constituents as distinct from equally weights. In other words, the *ISD* represents the contribution to portfolio volatility that may be attributable to some form of mean variance optimisation strategy, as distinct from a pure naive diversification strategy. When the *ISD* is negative it means that capitalisation weights had the effect of reducing portfolio volatility in relation to an equally weighted portfolio of the same constituents.

2.2. Decomposing the VCM

The method detailed in this section provides a simpler means of estimating the average variance and covariance than alternatives that estimate the historic VCM by calculating variance and covariance terms for all $N \times N$ elements in the VCM. Calculating the full historic VCM is particularly difficult for large portfolios in which constituents are not only being continually added and deleted, but also where their weights are changing with each relative change in share price. In the spirit of Figlewski (1997), the simplified method assumes that expected returns in the variance and covariance calculations are zero for all firms in the portfolio over each return observation period *(t)*.[6]

[6] The assumption of an expected return of zero, proposed by Figlewski (1997), or the contemporaneous risk free rate plus a long term average premium, such as that adopted by Campbell et al. (2001), are proxies for expected returns that would enable the procedure outlined in this paper to be adopted. When equity returns are measured

The standard formula for the variance of a portfolio of many assets can be decomposed into the average variance and covariance components for each return measurement period, without calculating $N \times N$ individual elements of the VCM. The standard formula for the value-weighted variance (*VWV*) of a portfolio of *N* assets is represented as

$$VWV = \sum_{i=1}^{N} w_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{i,j} \quad when\ i \neq j \tag{1}$$

where σ^2_i represents the variance of an individual portfolio constituent, w_i and w_j are the weights of firms *i, j,* $\sigma_{i,j}$ are the individual covariance terms for each pair of firms in the value-weighted VCM and *N* is the number of firms in the portfolio. Eq. (1) can be divided into the diagonal and off-diagonal elements of the VCM, referred to respectively as the value weighted average variance *(VAV)* and the value weighted average covariance *(VAC)* of constituent returns. On the right-hand-side of Eq. (1), the *VAV* is represented by the weighted summation of the variance terms while the *VAC* is represented by the double summation of the covariance terms. If the mean return is assumed to be constant and identical for all firms for any single return measurement period *(t)* the squared return of a portfolio (VWV_t) is equivalent to

$$VWV_t = \sum_{i=1}^{N} w_{i,t}^2 r_{i,t}^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,t} w_{j,t} r_{i,t} r_{j,t} \quad when\ i \neq j. \tag{2}$$

This is identical to Eq. (1), except that $r_{i,t}$ is substituted for σ_i, where $r_{i,t}$ is the security return over the time period *t* and *w* is the security weight in the portfolio at the beginning of period *t.*

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at daily frequencies or less, an identical mean return for all securities is a reasonable assumption, given that the realised variances are large in relation to any estimated mean return.

Single period estimates are liable to be very noisy; therefore, it is better to estimate realised *VWV* as an average of *T* squared portfolio returns, where *T* is greater than unity

$$VWV_T = \frac{1}{T}\sum_{t=1}^{T} VWV_t \tag{3}$$

where the VWV_t is the squared portfolio return measured over each of *T* intervals.

For any *t*, estimates of the average variance of portfolio constituent returns (VAV_t) can be calculated using

$$VAV_t = \sum_{i=1}^{N} w_{i,t}^2 r_{i,t}^2 . \tag{4}$$

When estimating the average covariance, it is common to calculate all the $N \times (N-1)$ individual covariance terms in the portfolio and then take an average. However, the same result can be achieved by simply subtracting the average constituent variance over each period *t* from the total portfolio variance as in

$$VAC_t = VWV_t - VAV_t = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,t} w_{j,t} r_{i,t} r_{j,t} \quad For\ i \neq j. \tag{5}$$

As with the value-weighted portfolio variance, it is more useful to estimate *VAV* and *VAC* over *T* periods, rather than over just a single period t as in Eq. (4) and Eq. (5). Therefore, single period estimates can be converted to *T* period averages using Eq. (6) and Eq. (7).

$$VAV_T = \frac{1}{T}\sum_{t=1}^{T} VAV_t \tag{6}$$

$$VAC_T = \frac{1}{T}\sum_{t=1}^{T} VAC_t \tag{7}$$

For multi-period estimates of VAC_T, this is much more computationally efficient than estimating the $N \times (N-1)$ paired covariance terms individually and summing them, as in the right hand side of Eq. (1).

The *VAV* and *VAC* of portfolio constituent returns can each be further subdivided into equally weighted and the incremental components. Eq. (8) shows the modifications made to Eq. (1) to calculate the variance of an equally weighted portfolio (*EWV*).

$$EWV = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\frac{\sigma_i^2}{N} + \left(\frac{(N-1)}{N}\right)\sum_{i=1}^{N}\ \sum_{j=1}^{N}\left[\frac{\sigma_{i,j}}{N(N-1)}\right] Where\ i \neq j \tag{8}$$

The equally weighted average variance *(EAV)* of constituent returns is equal to the sum of the equally weighted diagonal elements in the VCM and it calculated using Eq. (9). Single period estimates can be converted into *T* period estimates using the same principle as that detailed above for the *VAV* and *VAC*. As is the case with all variance estimates, the lower limit of the *EAV* is zero as the individual squared returns, or σ_i^2 elements, cannot be negative.

$$EAV = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\frac{\sigma_i^2}{N} \text{ and} \tag{9}$$

$$EAV_t = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\frac{r_i^2}{N} \tag{10}$$

The incremental average variance *(IAV)* is defined as the difference between the value-weighted and the equally-weighted sum of the diagonal elements in the VCM, as in

$$IAV = \sum_{i=1}^{N} w_i^2\sigma_i^2 - \left[\left(\frac{1}{N}\right)\sum_{i=1}^{N}\frac{\sigma_i^2}{N}\right] = VAV - EAV. \tag{11}$$

The incremental average variance can be either positive or negative depending upon whether or not the value-weighted average variance is greater or less than the equally weighted average variance.

The equally weighted average covariance *(EAC)* of constituent returns is equal to the equally weighted sum of all the off-diagonal elements in the equally weighted VCM. It is calculated using Eq. (12) which simply subtracts the *EAV* of constituent returns from the *EWV* of portfolio returns.

$$EAC = EWV - EAV = \left(\frac{(N-1)}{N}\right)\sum_{i=1}^{N}\sum_{j=1}^{N}\left[\frac{\sigma_{i,j}}{N(N-1)}\right] \text{ when } i \neq j \tag{12}$$

The *EAC* can be positive or negative, depending upon whether returns of firms in the portfolio are generally moving together or in opposite directions; it is generally accepted that most of the time *EAC* is positive.

This incremental average covariance *(IAC)* represents the difference between the market value-weighted and the equally weighted sum of all the off-diagonal elements in the VCM, and it is calculated by

$$IAC = VAC - EAC \tag{13}$$

$$= \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{i,j} - \left(\frac{(N-1)}{N}\right)\sum_{i=1}^{N}\sum_{j=1}^{N}\left[\frac{\sigma_{i,j}}{N(N-1)}\right].$$

Like the incremental average variance, the incremental average covariance can be positive or negative, depending upon whether the greatest weights are found in the largest off-diagonal elements in the VCM or the smallest off-diagonal elements in the VCM.

The incremental average variance and incremental average covariance can be combined additively to produce the incremental variance (*IV*) of the portfolio

$$IV = IAV + IAC. \tag{14}$$

IV is the difference between the variance of the equally weighted and the value-weighted portfolio, thus providing a measure of the net effect of portfolio concentration upon portfolio volatility. If the *IV* is positive, the concentration of the value-weighted portfolio has increased the realised volatility over and above that of an equivalent equally weighted portfolio of the same constituent firms, and vice versa if *IV* is negative at any given time *t*. For the convenience of the reader, a glossary of acronyms is provided in Table 4.

3 . Results and analysis of the data

3.1.1 Cumulative returns

Logarithms of the total dividend adjusted value and equally weighted versions of the FTSE 100 Index are plotted in Fig. 1. It is clear that the value weighted index began to out-perform the equally weighted index at an early stage in the data sample. Furthermore, this divergence in cumulative performance began to increase steadily from the late 1980s until the end of the study period. In fact, the cumulative difference during the twenty-one year study period amounts to an 80% out-performance of the value weighted index over its equally weighted counterpart. Clearly, the equally weighted portfolio would have been a much easier performance benchmark for active fund managers to beat than the value weighted FTSE 100 Index during this time.[7]

3.1.2 Equally weighted and incremental standard deviation of the FTSE 100 Index

The monthly incremental standard deviation is derived by subtracting the monthly standard deviation of the equally weighted portfolio from the monthly standard deviation of the value weighted portfolio. Although much smaller in magnitude than the equally weighted standard deviations, negative spikes of the incremental standard deviation, plotted in Fig. 2, have often occurred simultaneously with positive spikes in the equally weighted standard deviations and negative spikes (tail events) in returns, revealing that during volatility peaks, the monthly equally weighted standard deviation is greater than the monthly value weighted standard deviation of FTSE 100 Index returns.[8] Therefore, while Fig. 1 demonstrates that cumulative

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[7] Some analogy may be drawn between investing in value weighted indexes and a buy and hold strategy, whereas a more broad-based portfolio with a constituent weights closer to those of an equally weighted index can be compared with a contrarian strategy of selling winners, i.e. growing firms whose size has increased in relation to other firms in the investment universe and buying losers, firms whose weights have fallen in relation their peers. However, when new money is committed, or new large firms are added to an index, perhaps due to mergers, the value weighted strategy might be argued to have more in common with a momentum strategy of buying winners and selling losers. In addition, equally weighted indexes give a greater weight to small firms. Hence, they will perform better than value weighted indexes when small firms are doing relatively well compared to large firms. Irrespective of which strategy passive investing in a value weighted index most closely represents, the key issue of interest to investors is whether or not a value weighted stock index is *more* or *less* risky than an equally weighted index for a given level of return.

[8] This effect is particularly evident during the 19th October 1987 crash, the invasion of Kuwait by Iraq on the 2nd of August 1990, the period preceding the ERM crisis on the 16th September 1992, the Russian sovereign debt

returns of the value weighted index are greater than those of the equally weighted portfolio of constituents, Fig. 2 demonstrates that a value weighted portfolio is less risky than an equally weighted portfolio when the market as a whole is most volatile. This finding is consistent with the idea that large firms are generally less risky than smaller firms, perhaps they tend to have more stable cash flows resulting from more diverse income streams.

3.1.3 Sub-components of the FTSE 100 Index constituent variance covariance matrix

The time series of the monthly value weighted total portfolio variance and the incremental average variance of constituents are plotted in Fig. 3. It is clear that the monthly incremental average variance, i.e. the difference between the capitalisation weighted and equally weighted diagonal elements in the VCM, makes a negligible contribution to the total value weighted portfolio variance during the study period. Therefore, this is not likely to explain much of the incremental standard deviation plotted in Fig. 2, or the difference in cumulative returns between the value and equally weighted portfolios plotted in Fig. 1.

In fact, when the diagonal elements of the VCM, referred to as the equally weighted and value weighted average variance of constituents, were plotted on the same graph as the total portfolio variance, they were so small in relation to the total portfolio variance that they were difficult to distinguish from the x axis. Conversely, the equally weighted average covariance of constituents follows the path of the total portfolio variance more closely.[9] Such a finding

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default in August 1998, the terrorist attacks in September 2001 and the period leading up to the coalition operation in Iraq during March 2003.

[9] Figures for these particular time series are not reported here, although they are available from the author if requested.

is consistent with the principles of modern portfolio theory. Namely, that the majority of the variance in the returns of multi-firm portfolio is accounted for by the average covariance between constituent firm returns and not the average variance of constituent firm returns.

Given the relatively minor contribution of the average variance of constituent returns to total portfolio variance, it pays to focus on the incremental average covariance in the search for an explanation to the negative incremental standard deviation plotted in Fig. 2, as the incremental average covariance measures effects of capitalisation weighting upon the average covariance terms in the VCM. The time series of the incremental average covariance is plotted in Fig. 4, together with the total value weighted portfolio variance. Apart from a few exceptions, such as the summer 2002 bear market, the time series of the incremental average covariance of portfolio constituents appears to move in the opposite direction to the total value weighted portfolio variance, during periods of abnormal market volatility. When total value weighted portfolio variance spikes up, the incremental average covariance spikes down, but for the majority of the time when market volatility is stable, the incremental average covariance remains close to zero. Bear in mind that negative values of the incremental average covariance represent the extent to which the total value weighted portfolio variance has been reduced in comparison with that of the equally weighted portfolio by virtue of the constituent weights. Thus Fig. 4 illustrates the diversification benefits added by the capitalisation weighting of the FTSE 100 Index portfolio in a manner consistent with the principles of modern portfolio theory.

The net effect of the incremental average variance and covariance of constituent returns combined is illustrated by Fig. 5. This plots the monthly incremental variance of FTSE 100 Index returns together with the total monthly value weighted portfolio variance. The incremental variance comprises the time series of the monthly incremental average covariance and monthly incremental average variance combined additively, as in Eq. (14). It is clear that the diversification benefits of the, often negative, incremental average covariance generally outweigh any instances of positive incremental average variance. In fact, the combined incremental variance series follows an almost identical path to that of the incremental average covariance, plotted in Fig. 4.[10] Hence, the net effect of capitalisation weights is to reduce portfolio risk and improve portfolio diversification.

3.1.4 Single Index Regression model

Panel A of Table 2 displays the results of an OLS regression of daily total logarithmic returns of the equally weighted version of the FTSE 100 Index on the total returns of the value weighted FTSE 100 Index in the manner of a single index model. It is apparent from the statistically significant negative intercept coefficient α that the equally weighted portfolio has underperformed the value weighted FTSE 100 Index in a manner consistent with that indicated by Fig. 1. The daily α is negative with a t-statistic of 3.55%. If the negative α is annualised with an assumption of 250 trading days per year it amounts to an average market risk adjusted under-performance compared to the value weighted index of 250 basis points per year. In fact by annualising the 8,000 basis point *non*-risk adjusted excess return reported in the final column for the entire study period, it can be seen that the equally weighted portfolio underperformed the value weighted index by a logarithmic annual average of 380

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[10] One easy way to characterise the effect of the incremental variance on the total value weighted variance is to note that whenever the incremental variance is negative, it has had the effect of reducing the total variance by that amount, or if it had not been negative the total variance would have been that much greater. The converse is not true for positive values of the incremental variance, because the total value weighted variance plotted on the Fig. has incorporated both positive and negative values of the incremental variance.

basis points. The β coefficient at 0.97 is significantly less than unity with a t-statistic for $\beta \neq 1$ of 9.81, reflecting the greater influence of the smaller firms in determining the index returns. The correlation with the value weighted portfolio is high, with an R^2 of 93.4%, suggesting that reducing weights of the largest constituent firms adds little diversifiable risk to the portfolio and thus provides little, if any, diversification benefit in exchange for the under-performance. This is consistent with the evidence presented by Figures 4 and 5.

Panel B of Table 2 displays the standard deviation, maximum values, minimum values, kurtosis and skewness of daily returns for the value weighted FTSE 100 Index and equally weighted portfolio of constituents, respectively. The standard deviations of daily returns over 5,300 observations appear identical for the two series demonstrating that under normal conditions the value weighted index is no more risky than the equally weighted portfolio, despite the higher returns. Both the maximum and minimum daily returns observed over the whole sample are higher for the value weighted portfolio, indicating that the daily upside of the realised distribution has been higher while the downside has been smaller in magnitude. This is also reflected in the lower skewness observed in the equally weighted portfolio. Furthermore, the kurtosis is lower in the value weighted portfolio indicating that the probability of extreme values is less. In summary, Table 2 provides clear evidence that the equally weighted portfolio has under-performed its value weighted counterpart on a risk adjusted basis.

3.1.5 Size, style and industry factors

The persistence throughout the study period of the positive incremental returns arising due to capitalisation weights might appear to contradict the existence of a size effect demonstrated in the US market by authors such as Fama and French (1993) and subsequent studies of the UK market, whereby smaller firms have been shown to have greater risk adjusted returns than larger firms. This contradiction arises because smaller firms have a greater relative influence in equally weighted indices than they do in capitalisation weighted indices. Hence, if small firms on average have greater risk adjusted returns than large firms, a value weighted index would be expected to under-perform an equally weighted index, all other things being equal. However, studies of the size effect subsequent to Fama and French (1993) indicate that it may be temporally variable in the UK (Dimson et al. 2003) and potentially prone to measurement error (Lee et al. 2004) in the UK, and in the US market (Downs and Ingram, 2000). Furthermore, most US and UK studies of the size effect use benchmarks such as the CRSP Total Market Index or the FTSE Allshare Index. Although the majority of their value is made up of a relatively small number of large firms, both of these indexes contain a relatively large numerical proportion of small constituents, many of which are not sufficiently liquid to form part of an investable universe for a large institutional portfolio. In contrast, even the smallest firms in the FTSE 100 Index are large by the standards of the market as a whole. Nonetheless, the few largest firms in the FTSE 100 Index are many times larger than the smallest constituents and may be described as a subgroup of internationally diversified 'mega firms'. Dimson et al (2002 p. 129) report the differences in annual returns for a recreated version of the capitalisation weighted and equally weighted FTSE 100 Index from 1900 through 2000. For the first fifty years, the equally weighted index out-performed the value weighted index by an average of 0.5% per year. However, over the whole period, there was little evidence of a consistent size effect in the 100 largest constituents of the UK equity market. Perhaps the small number of mega firms account for the majority of the incremental returns, variance and covariance in the VCM of the FTSE 100 Index portfolio since 1984. If this were the case, their disproportionate effect upon the returns of the FTSE 100 Index, and even the UK equity market as a whole, might not have been detected by previous studies of size and style effects that tend to calculate average returns of size and style ranked portfolios categorised by percentiles of firm sizes.[11]

Nonetheless, in an attempt to explain monthly incremental returns (*IR*), they were regressed upon a size factor, a style factor and the market factor in four model combinations over the period for which relevant factor data was available, namely 1st January 1987 through to the 31st December 2004. The market factor was the total monthly return of the FTSE Allshare Index including dividends less the one month Treasury bill return. The size factor was derived by subtracting the total monthly returns of the FTSE Small Cap Index (excluding Investment Trusts) from the total monthly returns of the FTSE 100 Index.[12] The style factor

[11] Percentiles used vary between studies published depending on the size and characteristics of the respective market. Although they tend to be numerically biased in favour of small firms they still usually account for the minority of the total market capitalisation of the respective markets. For example, according to the London Stock Exchange file of listed firms on the 30th November 2005, the sum of the market capitalisations of all firms larger than the UK median firm size accounts for 98% of the capitalisation of all the firms with a UK listing on the London Stock Exchange. In fact the aggregate of the small firm portfolios used by Dimson et al (2003) accounted for just 6% of the total capitalisation of the UK market.

[12] The FTSE Small Cap Index Excluding Investment Trusts is a capitalisation weighted share price index of all firms that are constituents in the FTSE Allshare but not included in 350 largest firms listed on the London Stock Exchange (LSE). Investment trusts are excluded to avoid double counting. The FTSE Allshare index represents more than 95% of the value of the entire UK main equity market. It excludes the alternative investment market (AIM) which accounts for 1% of the equity market capitalisation of all firms listed on the LSE. The 1st January 1987 is the first date that both FTSE Small Cap total returns (RI) and FTSE Style price only (PI) daily returns are available. Total returns were for the FTSE Style Indices are not available until the 18th August 1997. Therefore, the style factor was calculated using capital only returns.

was derived by subtracting the monthly returns of the FTSE 100 Value Index from the monthly returns of the FTSE 100 Growth Index.[13] Coefficients of a fifth model described by

$$IR_t = \alpha + \sum_{I=1}^{I=10} \lambda_{1,10} I_{1t,10t} + \varepsilon_t \tag{15}$$

were estimated to investigate the possibility that the incremental returns *(IR)* might be explained by the bias of the index to towards certain industries. The industry factor returns ($I_{1,..10}$), represented by the ten "New FTSE Economic Groups" which make up the FTSE Allshare Index.[14] Hence the market factor is replaced by the industry factors in the fifth model. The results of the five regression models are presented in Table 3.

In Table 3, Panel A presents the results of a basic model of incremental returns on an intercept. The significant intercept t-statistic indicates that the mean monthly incremental return is significantly different from zero at 0.33% which annualises to 3.96 based on logarithmic returns. When the excess returns on the FTSE Allshare Index are added to the model (panel B), the size factor (panel C) and the style factor (panel D), the mean incremental return represented by the intercept coefficient is still significantly different from

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[13] The calculation methods and rules for the FTSE Style Indices are detailed in the Guide to the FTSE Global Style Indices available online at FTSE International. The value – growth ranking system takes into account price to book, price to sales, price to cash flow ratios and dividend yields to provide a benchmark for value and growth investors respectively.

[14] The ten FTSE Allshare Economic Groups listed in Table 4 replaced the former Six Economic groups on the 1st April 1999. Back histories of the ten groups are available from the 1st January 1986, apart from the Utilities group that begins on the 8th December 1986. Multifactor models start at the 1st of January 1987 when data for the FTSE Style Indices first becomes available.

zero, while the adjusted R^2 indicates that market, size and style factors only explain about 14% of the incremental returns. Coefficients on the market, size and style factor are negative indicating that the value weighted index outperforms the equally weighted portfolio during down markets and periods when small stocks and value stocks under perform large cap growth stocks. In fact, Dimson et al. (2003) report that size and value rankings are negatively correlated resulting in a predominance of value stocks in small capitalization portfolios.

Panel E reports the results of model V, which accounts for the influence of industry excess returns represented by the ten New FTSE Economic Groups. Industry model coefficients are listed in decreasing order of their influence on the adjusted R^2, which increases from 14% to 67% compared to model IV. Although adding industry excess returns to the list of model variables considerably increases the model explanatory power, the intercept coefficient is still positive and significantly different from zero confirming that the value weighted FTSE 100 Index outperforms its equally weighted counterpart even after accounting for market, size, style and industry factors. All industry model coefficients are significantly different from zero at the 5% level apart from “Financials”. Monthly returns for “Resources”, “Non Cyclical Consumer Goods”, “Non Cyclical Services” and “Financials” are all positively associated with the monthly incremental returns, the rest are negatively associated. Significant positive association with an industry factor implies that incremental returns may be derived from large firms in those industries. Negative coefficients on industry factors, may imply that incremental returns are not derived from firms in those industries and that those industries are populated more by smaller firms that would have a relatively greater influence on an equally weighted index than on a capitalisation weighted index. Results of an additional model that included market, size, style and industry residual returns were also examined. However, adding the additional variables only increased the adjusted R^2 by 1% to 68% while the Schwarz criterion was smaller in magnitude at 6.51 indicating that the parsimonious model should be favoured. Hence the results of the more general model are not reported here. Therefore, the implication is that industry factors explain the majority of the incremental returns (67%), size and style factors explain 1% and the remaining 32% remains to be explained by other factors. It may be that larger firms have more defensive characteristics, falling less than average in down markets, but rising less than average during up markets.

4 . Conclusions

This study demonstrates the beneficial contribution of capitalisation weights to the portfolio diversification and returns of the FTSE 100 Index. The contribution to diversification is attributed to the below average covariance characteristics of the largest constituent firms ranked by market capitalisation. This attribution is achieved by decomposing the variance covariance matrix of daily portfolio constituent returns into the average variance and covariance components that are conditional upon capitalisation weights and those that are not.

Over the period from January 1984 to December 2004, market capitalisation weights have added over 8,000 basis points of return to the FTSE 100 Index compared to an equally weighted portfolio of the same constituents. Furthermore, the total volatility (risk) of the capitalisation weighted index was less during periods of market stress that resulted in negative return tail events. Given that an equally weighted index is effectively an index with weights capped at 1/n, proposals by some in the fund management industry to cap the weights of the largest firms in benchmark indexes at arbitrary levels, such as 5%, should be questioned unless more convincing evidence of the benefits to passive investors, or those benchmarked to the respective index, can be found. Indeed, the evidence presented here with respect to the FTSE 100 Index clearly demonstrates that the equally weighted benchmark index is a much easier performance threshold for active managers to beat than the value weighted counterpart, as it has lower returns and potentially greater risk during times of market stress. In the face of suggestions that fundamental weights, capped weights or equal weights may be preferable to capitalisation weights, the author stands in defence of capitalisation weights on the premise of “innocent until proven guilty”. This is consistent with the views expressed by authors such as Dimson et al (2002) and Haberle and Ranaldo (2005) to the effect that inclusive capitalization weighted indexes adjusted for free float are the most suitable benchmarks to measure the aggregate performance of a market or sector. The findings will be of interest to stock index providers aiming to supply appropriate model portfolios for passive investors, or active manager benchmarks. They are also relevant to investors’ asset allocation decisions because they highlight the importance of the covariance between the returns of the dominant securities. For example, a semi-passive investor wishing to hold a proxy for sections of the UK market portfolio, such as the FTSE 100 Index, might question whether or not the UK market portfolio is more risky as a result of increases in concentration. The results of this study indicate that it is not. Likewise, active investors might want to know if the risk of their portfolios could be reduced by down-weighting the dominant FTSE 100 Index constituents. In fact, the results suggest that such a strategy may increase risk if the incremental components of realised volatility are negative in the FTSE 100 Index. Therefore, only the possession of superior knowledge concerning the average covariance or expected returns of the constituent securities in relation to the average covariance of all the securities in the investment universe could justify this decision. Supporters of the efficient markets hypothesis would argue that such superior knowledge is difficult to obtain.

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Table 1. Five largest constituents of the FTSE 100 Index by market capitalisation on the 3rd August 2005 and correlations between their daily returns to December 2004

Company name	*%*	*Cum %*	*BP*	*SHELL*	*HSBC*	*VODAFONE*
BP	10%	10%	*Cross Correlations*			
ROYAL DUTCH SHELL (A shares plus B shares combined)	9%	19%	0.69			
HSBC	8%	27%	0.32	0.36		
VODAFONE	7%	34%	0.24	0.26	0.37	
GLAXOSMITHKLINE	6%	40%	0.29	0.33	0.27	0.27

Table 1 ranks the top five constituent firms of the FTSE 100 on August 3rd 2005 by market capitalization, showing the percentage of weight in the index and the cumulative percentage weight. In addition, cross correlations between the daily returns of the top five firms from the date of inclusion in the index to January 2005 are presented. Source: Thomson Financial Datastream. Note: the top ten firms account for 54% of the index.

Table 2. Regression of equally weighted portfolio of FTSE 100 Index constituent daily returns on the value weighted FTSE 100 Index returns

Panel A							
α	T-stat α	β	T-stat β	T-stat $\beta \neq 1$	R^2	RMSE	VWFTSE 100 – EWFTSE 100
-0.01%	-3.55	0.97	274.17	9.81	93.4%	0.3%	-80.1%

Panel B					
	Standard deviation of daily returns	**Maximum daily return**	**Minimum daily return**	**Kurtosis of daily returns**	**Skewness of daily returns**
Value weighted FTSE 100 Index	1.05%	7.7%	-13.6%	9.8	-0.7
Equally weighted portfolio of FTSE 100 Index constituents	1.05%	7.3%	-15.3%	13.9	-1.0

Panel A of Table 2, reports the α coefficient, β coefficient, t statistic of the β coefficient in relation to zero and the t statistic of the β coefficient in relation to unity, for an equally weighted portfolio of FTSE 100 Index constituent daily returns regressed on the value weighted FTSE 100 Index portfolio of the same constituents over the entire study period. The cumulative excess return of the value weighted return over the equally weighted return during the entire study period is also reported in the final column. Panel B, reports the standard deviation, maximum, minimum, kurtosis and skewness of daily returns over the entire study period January 1984 - January 2005 for the value weighted FTSE 100 Index and the equally weighted portfolio of Index constituents respectively.

Table 3 Size, style and industry factor regressions based upon regression models with the monthly incremental return *(IR)* as the dependent variable

Panel A: model I $IR_t = \alpha + \varepsilon_t$			
	R-squared	***Adjusted R-squared***	***Schwarz criterion***
	0.0000	0.000	-5.61
	Coefficient value	***t-Statistic***	***Prob.***
Intercept	0.33%	3.78	0.00
Panel B: model II $IR = \alpha + \beta_1(R_{mt} - r_f) + \varepsilon_t$			
	R-squared	***Adjusted R-squared***	***Schwarz criterion***
	0.12	0.12	-5.72
	Coefficient value	***t-Statistic***	***Prob.***
Intercept	0.36%	4.46	0.00
Market Excess Return $(R_m - r_f)$	-0.10	-3.00	0.003
Panel C: model III $IR_t = \alpha + \beta_1(R_{mt} - r_{ft}) + \beta_2 SMB_t + \varepsilon_t$			
	R-squared	***Adjusted R-squared***	***Schwarz criterion***
	0.15	0.14	-5.72
	Coefficient value	***t-Statistic***	***Prob.***
Intercept	0.37%	4.49	0.00
Market Excess Return	-0.11	-3.23	0.00
Size Factor Small minus Big (SMB)	-0.06	-2.52	0.01
Panel D: model IV $IR_t = \alpha + \beta_1(R_{mt} - r_{ft}) + \beta_2 SMB_t + \beta_3 VMG_t + \varepsilon_t$			
	R-squared	***Adjusted R-squared***	***Schwarz criterion***
	0.16	0.14	-5.71
	Coefficient value	***t-Statistic***	***Prob.***
Intercept	0.38%	4.62	0.00
Market Excess Return	-0.11	-3.37	0.00
Size Factor: SMB	-0.06	-2.32	0.02
Style Factor: Value minus Growth (VMG)	-0.07	-1.71	0.09
Panel E: model V $IR_t = \alpha + \sum_{I=1}^{I=10} \lambda_{1,10} I_{1t,10t} + \varepsilon_t$			
	R-squared	***Adjusted R-squared***	***Schwarz criterion***
	0.68	0.67	-6.52
	Coefficient value	***t-Statistic***	***Prob.***
Intercept	0.28%	4.21	0.00
I_1***: FTSE Cyclical Services***	-0.17	-5.76	0.00
I_2***: FTSE General Industries***	-0.06	-2.08	0.04
I_3***: FTSE Basic Industries***	-0.05	-2.05	0.04
I_4***: FTSE Cyclical Consumer Goods***	-0.04	-1.95	0.05
I_5***: FTSE Non Cyclical Services***	0.12	7.84	0.00
I_6***: FTSE Non Cyclical Consumer Goods***	0.11	6.25	0.00
I_7***: FTSE Resources***	0.09	5.91	0.00
I_8***: FTSE Information Technology***	-0.02	-2.05	0.04
I_9***: FTSE Financials***	0.04	1.46	0.15
I_{10}***: FTSE Utilities***	-0.06	-3.16	0.00

Table 3 reports the results of models using 227 observations of monthly data each derived from twenty trading days of non-overlapping daily data. The proxy for the market excess return is the monthly FTSE Allshare Index total return minus the risk free rate (logarithmic one-month London Treasury Bill returns). Monthly industry excess returns *(I)* total excess returns over the risk free rate of the ten New FTSE Economic Groups that together make up the FTSE Allshare Index. Industries and their model coefficients are listed in decreasing order of their influence on the model adjusted *R* squared values.

Table 4 Glossary of abbreviations

Panel A: Glossary of abbreviations of the VCM sub-components		
VCM sub-component	***Abbreviation***	***Calculation***
Value weighted total variance of portfolio returns	*VWV*	$VWV = \sum_{i=1}^{N} w_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{i,j}$ *when* $i \neq j$
Equally weighted total variance of portfolio returns	*EWV*	$EWV = \left(\frac{1}{N}\right)\sum_{i=1}^{N} \frac{\sigma_i^2}{N} + \left(\frac{(N-1)}{N}\right)\sum_{i=1}^{N} \sum_{j=1}^{N} \left[\frac{\sigma_{i,j}}{N(N-1)}\right]$
Value weighted average variance of constituent returns	*VAV*	$VAV = \sum_{i=1}^{N} w_i^2 \sigma_i^2$
Value weighted average covariance of constituent returns	*VAC*	$VAC = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{i,j}$ = *VWV - VAV*
Equally weighted average variance of constituent returns	*EAV*	$EAV = \left(\frac{1}{N}\right)\sum_{i=1}^{N} \frac{\sigma_i^2}{N}$ *and* (9) $EAVt = \left(\frac{1}{N}\right)\sum_{i=1}^{N} \frac{r_i^2}{N}$
Incremental average variance of constituent returns	*IAV*	*IAV = VAV - EAV*
Equally weighted average covariance of constituent returns	*EAC*	*EAC = EWV - EAV*
Incremental average covariance constituent returns	*IAC*	*IAC = VAC - EAC*
Incremental portfolio variance	*IV*	*IAV + IAC*

Panel B: Mapping of the ten new FTSE Allshare Economic (Industry) Groups used in this study with the six former economic groups (Source: Thomson Financial Datastream)

Six Former Economic Groups	***Mnemonic***	***New Economic Groups***	***Mnemonic***
Resources	RESRFTA	Resources	FTSERSR
		Basic Industries	FTSEBIN *!
General Industries	GENMFTA	General Industries	FTSEGIN
Consumer Goods	CGDSFTA	Cyclical Consumer Goods	FTSECGD
		Non-Cyclical Consumer Goods	FTSENCG *!
Services	SERVFTA	Cyclical Services	FTSECSV
		Non-Cyclical Services	FTSENSV *!
Utilities	UTILFTA	Utilities	FTSEUTL
Financials	FINSFTA	Financials	FTSEFIN
*! New Index		Information Technology	FTSEIMT *!

Logged FTSE 100 Index and an equally weighted portfolio of the same constituents

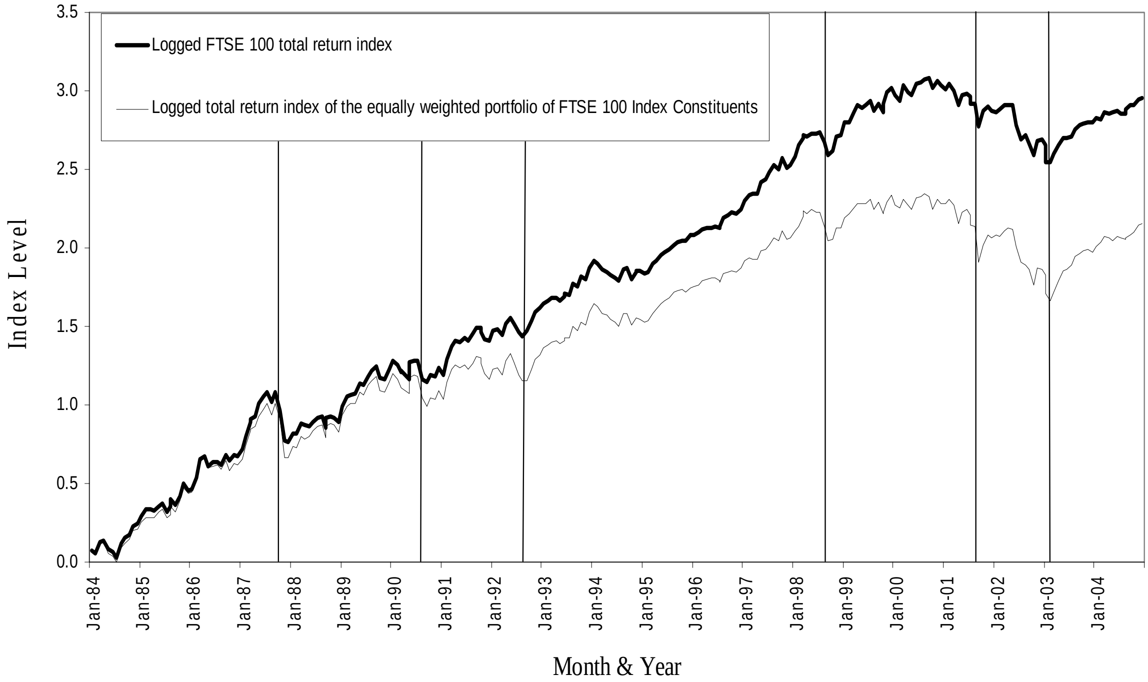

Fig. 1. Cumulative monthly logarithmic returns of an equally weighted portfolio of FTSE 100 constituents (thin line) and the value weighted FTSE 100 Index (bold line). Vertical lines represent major political and economic events such as the 1987 market crash, Saddam Hussein's invasion of Kuwait in August 1990, uncertainty surrounding Britain's exit from the Exchange Rate Mechanism (ERM) in 1992, Russia's sovereign debt default in August/September 1998, the terrorist attacks of September 2001and the coalition operation in Iraq beginning in March 2003.

Monthly equally weighted and incremental standard deviation of the FTSE 100 Index

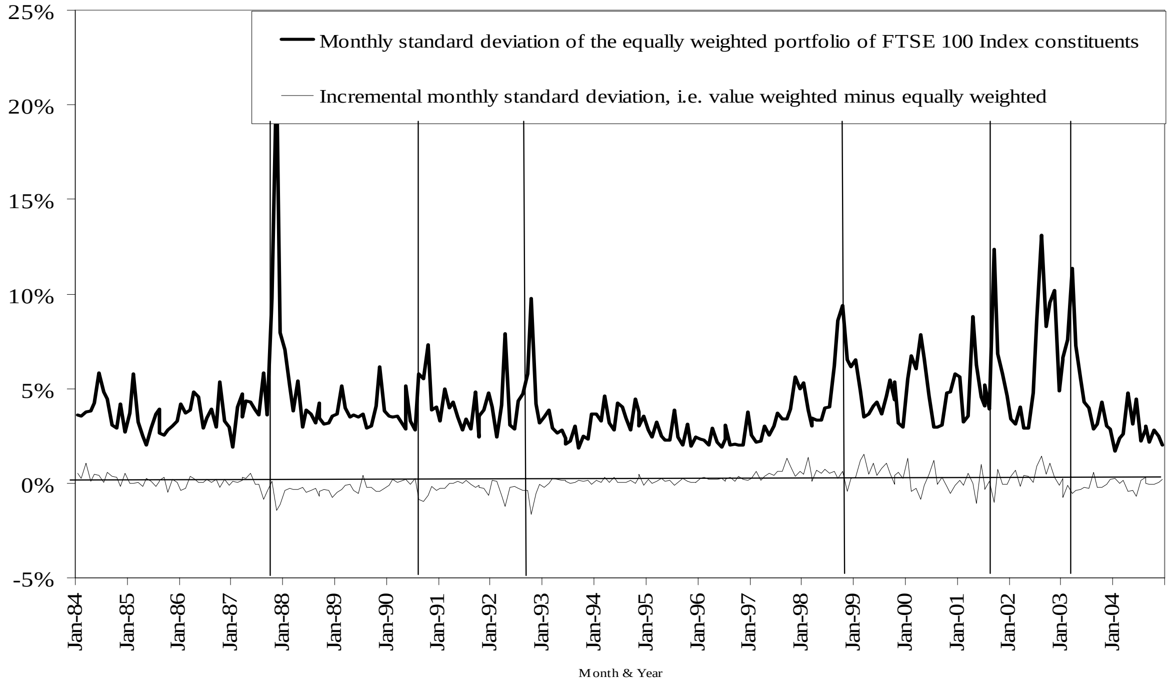

Fig. 2. Total monthly standard deviation (bold line) and the monthly Incremental Standard deviation (thin line) of the equally weighted FTSE 100 Index returns. Each data series comprises discrete non-overlapping estimates each generated using twenty trading days of index and constituent total return data. Vertical lines are as for Fig. 1.

Total variance and incremental average constituent variance of the FTSE 100 Index

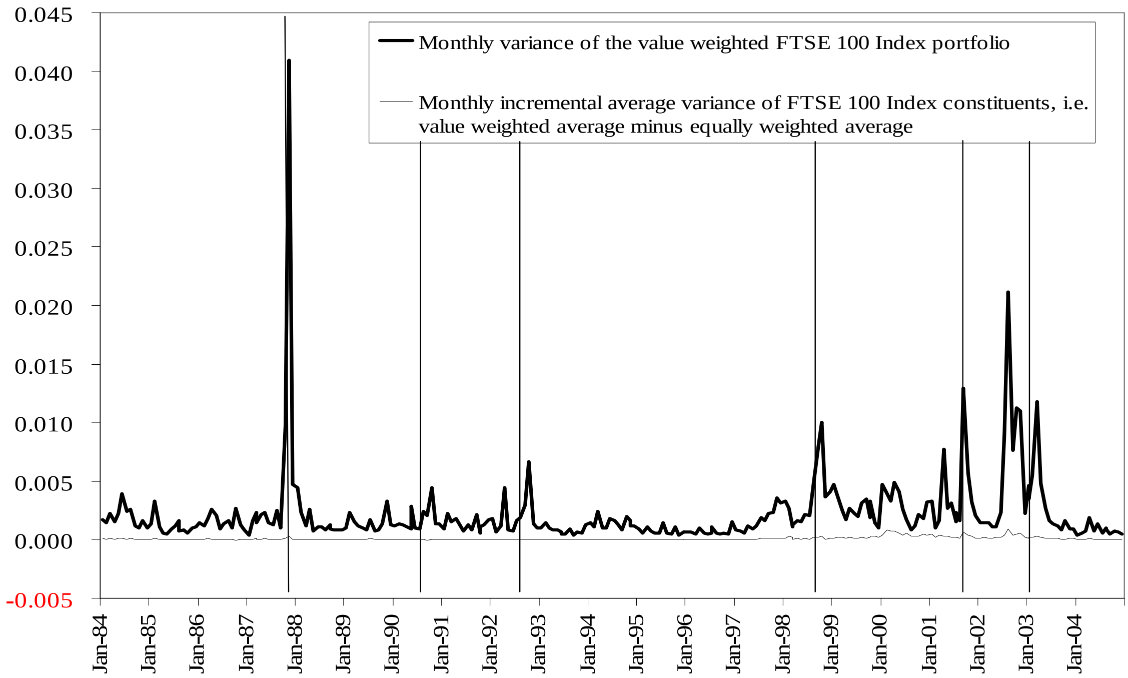

Fig. 3. Total monthly variance (bold line) of FTSE 100 Index returns and incremental average variance of constituents (thin line). Each data series comprises discrete non-overlapping estimates each generated using twenty trading days of index and constituent total return data. Vertical lines are as for Fig. 1.

Total variance and incremental average covariance of the FTSE 100 Index

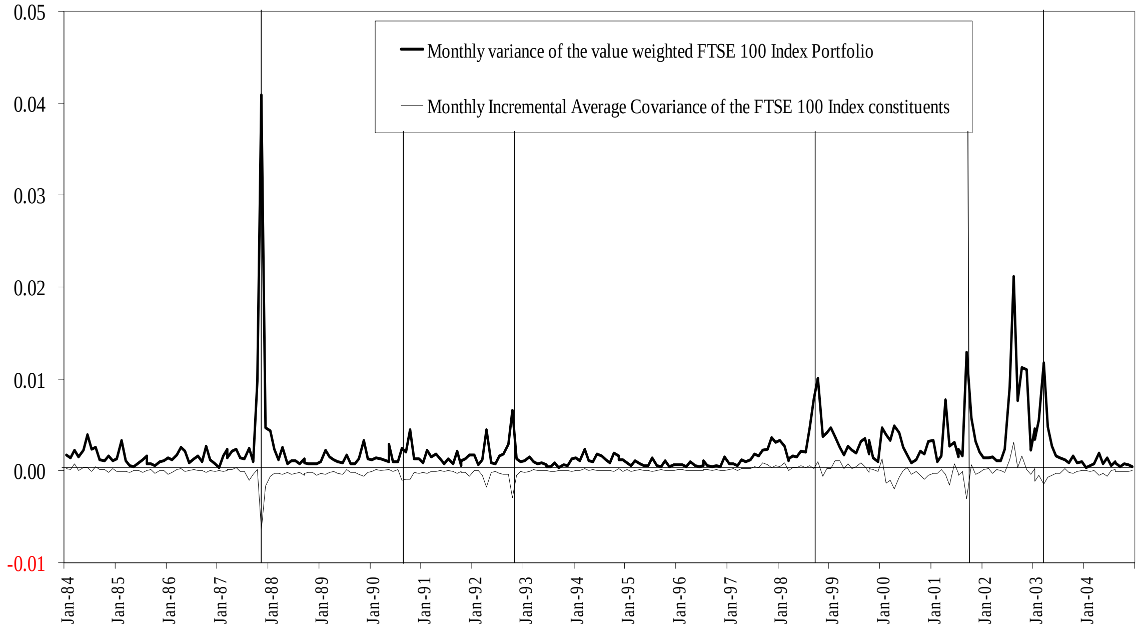

Fig. 4. Total monthly variance (bold line) of FTSE 100 Index returns and incremental average covariance of constituents (thin line). Each data series comprises discrete non-overlapping estimates each generated using twenty trading days of index and constituent total return data. Vertical lines are as for Fig. 1.

Total variance and incremental variance of the FTSE 100 Index

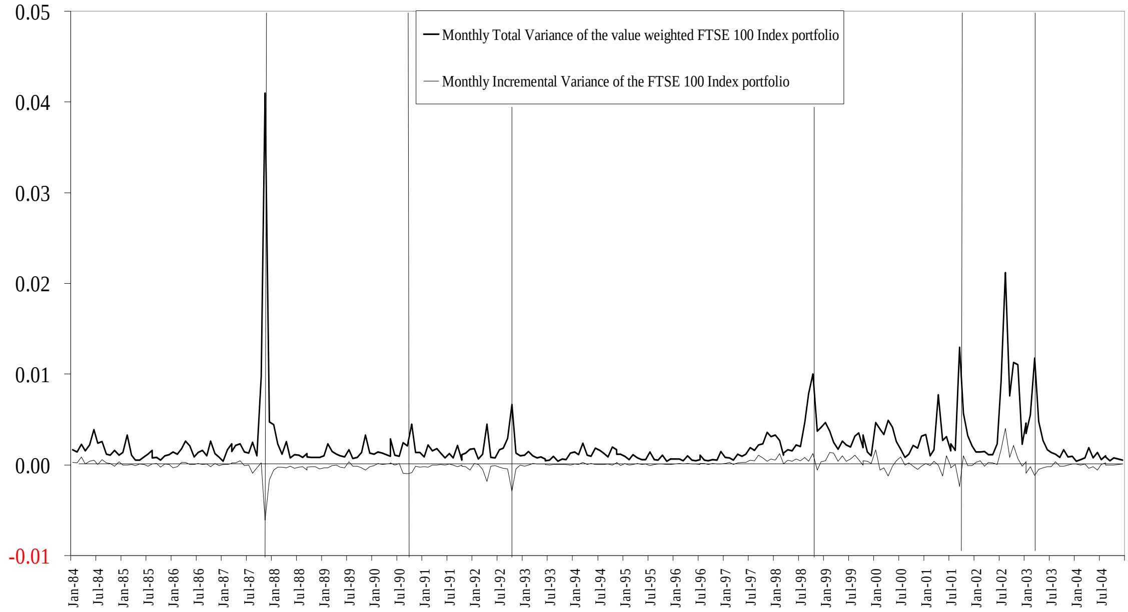

Fig. 5. Total monthly variance (bold line) of FTSE 100 Index returns and incremental variance of constituents (thin line). Incremental variance is derived by adding together the incremental average covariance and incremental average variance, or alternatively by subtracting the variance of the equally weighted portfolio of FTSE 100 Index constituent returns from that of the value weighted Index. Each data series comprises discrete non-overlapping estimates each generated using twenty trading days of index and constituent total return data. Vertical lines are as for Fig. 1.