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# Fundamental indexation revisited: New evidence on alpha

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ABSTRACT

This study proposes indexing strategies representative of the equity market and based on readily available accounting information. In contrast to the previous literature, we discard balance sheet variables and instead develop two indices that revolve solely around income statement and dividend measures. We find that these indices outperformed the FTSE 100 by 3% on an annual basis over the last 25 years, whilst delivering similar or lower volatility. The constructed indices overlap by 90% with the FTSE 100, in terms of their total market capitalisation and constituent members. They have positive and significant alphas in 3- and 4-factor performance attribution models, showing that the performance cannot be explained by value, size, market beta or momentum tilts alone.



## 1. Introduction and motivation

This study focuses on developing a superior indexation approach using readily available accounting information and circumventing the limitation of size-only investment criteria. Since the advent of exchange-traded funds (ETFs), not only has the number of strategies available to small and institutional investors experienced a significant upsurge, but fees and costs have also dropped significantly. These revolutionary products have drastically improved passive management services, as they offer a clear investment objective and a transparent benchmark strategy, along with stringent regulatory supervision and the benefits of an exchange-listed vehicle. At the same time, active managers could take advantage of these packaged products, gaining a cost-effective exposure to a broad range of asset classes, whilst the introduction of active ETFs filled the gap by offering enhanced returns within a well-regulated framework. With time, markets have blended active and passive investments until the boundary is no longer neatly defined. It is clear that this 3-trillion dollar industry[1] has reshaped investment approaches from retail to institutional investors and, given its vast diversity, deserves attention and deeper understanding.

The capitalisation-weighted investment approach has always been the core building block for the passive portfolio management community and the highest proportion of the money invested in passive investment is tied to value-weighted indices. Over the last decade, the traditional strategy of investing in the market portfolio has been challenged by the so-called "smart beta" strategies, which, although consistent with rules-based investments, outperform the benchmark by capturing market inefficiencies. Furthermore, purely passive investments in derivatives markets may lead to low long-term returns. Good examples are the ETFs that invest in the front-month futures contract (e.g. oil ETFs) that "bleed" money if the rolling of the investment takes place in a contango market environment (i.e. the next futures contract is more expensive).

This study aims to put forward superior indexing strategies representative of the UK market based on readily available accounting information, which, by weighting companies differently from their market valuation, eradicates the performance drag and offers higher risk efficient returns. Different from the existing literature, we eschew balance sheet measures and propose two indices that revolve solely around income statement (P&L) and dividend measures. The income and dividend-based indices are intuitive and simple to construct, have reduced exposures to standard risk factors (size, value and market risk) and avoid strategy construction based on book values. Further, the pure dividend-based approach, which we also employ, does not use accounting variables at all, which avoid the subjectiveness[2] of such measures. Dividends (and earnings per share) do not suffer from creative accounting and are comparable across different legislations

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[1] Source: ETFGI data, see http://etfgi.com/publications/reports.

[2] Accounting measures may be misleading due to different accounting conventions across countries and the existence of creative accounting.

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and accounting standards. As such, our findings are generalizable and the results more likely to be robust when tested in different economies. We find that these accounting based weighting schemes deliver an annual outperformance of between 2.39% and 3.59% over the FTSE 100 and up to twofold increases in the Sharpe and Sortino ratios. The procedure employed, which is deliberately left unconstrained, leads to very favourable results. Most notably, we find that our index designs have positive and significant Fama-French 3-factor and Carhart 4-factor alphas. The indices maintain an overlap with the FTSE 100 of approximately 90% in terms of total market capitalisation and constituent members. We also benchmark the results to Arnott, Hsu, and Moore's (2005) fundamental indexing design, using a data sample of UK equities over a period that contains the 2008 financial crisis. The suggested strategies also comfortably outperform Arnott et al. under a variety of metrics.

Overall, the exercise contributes to the literature by providing an in-depth analysis of the virtues of fundamental *non-balance sheet based* indices compared to their cap weighted counterparts. Findings show that fundamental strategies work in the UK stock market and are clearly better than cap-weighted indices. In particular, unlike other Market Value Indifferent (MVI)[3] designs previously proposed in the literature, our fundamental indices are able to generate significant 3- and 4-factor alphas. By disregarding balance sheet measures and focusing on Profit and Loss variables to construct the indices, this study differentiates from previous research, indicating that our indexation strategy significantly outperforms the traditional fundamental indexing schemes and offers lower exposure to size and value factors.

The rest of this paper is organised as follows. Section 2 describes the existing academic literature on market value indifferent (MVI) indexation, including the theoretical debate and empirical evidence. Section 3 outlines the data collection process and the index construction methodologies proposed here. Section 4 presents the results of the empirical test run on the UK FTSE All Share index. Sections 5 and 6 depict, respectively, robustness tests of the results and the performance attribution. Finally, Section 7 concludes and analyses possible implications of the study.

## 2. Existing research on price-indifferent indexation schemes

### 2.1. Indexation schemes

#### 2.1.1. Cap-weighted indexing

The most common indexation methodology, capitalisation weighting, provides a number of advantages. First, it offers an accurate representation of the available investment opportunities, as their weighting corresponds to their dimension on the market. Second, these indices are market-clearing portfolios, i.e. there is a balance between demand (investors) and supply (shares). Any deviations from CW design would, by construction, mean that the portfolio would not be able to encompass the whole market. In other words, if every single market participant invests according to cap weights, there would be no securities left unsold, i.e. the primary markets would be cleared as each investor's portfolio would hold companies in the same proportions as the whole market (absolute weights would differ, but relative weights would be equal). On the other hand, should all stockholders invest in a single alternative scheme, there would be an imbalance between the demand for shares (implied by the weight assigned by their strategy) and their supply (given by the market capitalisation of each listed firm). Third, they represent the performance of the average investor, which makes it a reasonable investment benchmark. The latter is a direct consequence of the second advantage, namely the market-clearing characteristic. Lastly, capitalisation weighted portfolios do not require rebalancing in components' weights as prices fluctuate unless the index constituents change (index re-composition events, additions or deletions). Thus the low turnover figures of these portfolios, presented in Section 3, should not be surprising.

Since, from its definition under the capital asset pricing model (CAPM), the market portfolio comprises all risky assets with weights in the proportions that they occur in the market, cap weighted indices have been used extensively as market portfolio proxies. Accordingly, stock weights in the market portfolio coincide with company weights in the CW index. This *modus operandi* is still practiced today notwithstanding Roll (1977) arguing that the true market portfolio cannot be measured.

Despite the widely reported benefits of cap–weighting, the strategy has faced important criticisms by previous research; in the context of securities valuation, stock prices may differ from their fair fundamental values by random noise.[4] By definition, overvalued stocks will have experienced positive noise, whereas undervalue stocks experienced negative noise. As Treynor (2005) suggests, when market capitalisation weighting (CW) is employed to construct an investment portfolio, larger bets are placed on over-valued companies relative to their unobservable fair values, and smaller bets are placed on under-valued ones.[5] Cap-weighted indices do not disentangle company weighting from valuation, as the former is directly related to the latter, and this peculiarity causes the (unobservable) noise in stock prices to be embedded twice in the portfolio: in the purchase price and in the weighting. Effectively, CW mirrors market values and echoes them in the constituent proportions, thereby provoking a further amplification of any price noise. Therefore, perhaps unsurprisingly, a study by Chen, Chen, and Bassett (2007) has shown that where cap weights are magnified (cap squared), returns worsen, whereas, when weights are smoothed (via roots, equal weight or smoothed averages), performances improve.

Numerous other studies starting from Mayers (1976) have reported limitations of the CAPM and the use of cap weighting indices as market portfolio proxies. Ross (1978), Gibbons (1982), Zhou (1991), Fama and French (1998) and Dalang, Osinski, Marty, and Dalang (2001), to cite but a few, all reject the mean-variance efficiency of capitalization weighted indices. Accordingly, these findings imply an *ex-ante* inefficiency of the whole passive investment industry (Branch & Cai, 2010; Haugen & Baker, 1991). A new strand of literature has since begun investigating price indifferent strategies that could alleviate this natural performance drag and develop better ways to index, i.e. to construct portfolios that offer higher risk-adjusted returns.

Arnott et al. (2005) were perhaps the pioneers of the smart beta strategies.[6] Many others, including Amenc, Goltz, Lodh, and Martellini (2012), then followed. Roll and Ross (1994), in seeking a superior indexation methodology, concluded that: (i) ex ante identification is impossible; and (ii) cap-weight indices lie only 22 basis points away from the efficient frontier. Although conceptually different, these strategies' common denominator is their attempt to provide a clear and simple methodology (in the spirit of passive investing) that deviated from the more popular CW schemes (resembling active strategies).

#### 2.1.2. Optimisation based indexing

In the last decade the literature on new indexation methodologies has been very prolific and two coexisting strands of indexing schemes, following the Chow, Hsu, Kalesnik, and Little (2011) classification,

[3] Throughout the paper, we will refer to MVI or price-indifferent strategies interchangeably to encompass any indexation design that deviates from cap weighting.

[4] Of course, deviations from fundamentals may also take place for other reasons such as the limits to arbitrage discussed, for example, by Shleifer and Vishny (1997).

[5] This statement assumes that the true company fair value, given by the present value of the expected income flow, is unknown by investors.

[6] Their Research Affiliates Fundamental Index™ (Ticker: PRF) includes 1000 US stocks and has outperformed the Russell 1000 index by 87 basis points per year, as of 03/31/2016, since inception (source: www.invescopowershares.com).

have emerged: *optimisation based* and *heuristic* strategies. Optimisation based strategies take the CAPM and modern portfolio theory a step further. In the light of the criticisms described above, these strategies retain the general framework, meaning that they are still mean variance optimizers (MVO), yet they twist some of the assumptions in order to address the shortfalls highlighted. Although, theoretically, MVO are an excellent way to form ex ante efficient portfolios, the estimation of the two required inputs i.e. expected returns and expected covariances, can be very challenging. Furthermore, Chopra and Ziemba (1993) and Michaud (1989) report that forecasting errors in the input parameters translate into meaningfully reduced performance of the output portfolio.

The most prominent MVO strategies include the approaches of minimum variance, maximum diversification, risk efficiency and relative risk optimisation. In the context of a minimum variance strategy, Haugen and Baker (1991) and Clarke, De Silva, and Thorley (2006) overcome the inherent estimation difficulties by implicitly assuming constant expected returns across all stocks. The maximum diversification strategy introduces the diversification ratio as the main driver of portfolio construction; Choueifaty and Coignard (2008) link the volatility of a stock to its premium return by a simple linear relationship and determine companies' weights in the index by optimizing the portfolio Sharpe ratio. The risk efficient strategy is in line with the traditional CAPM theory, and maintains the same explicit risk return efficiency target by maximising the Sharpe ratio (Amenc, Goltz, Martellini, & Retkowsky, 2011). The strategy of model and risk optimisation involves non-mutually exclusive portfolio construction methodologies with the explicit aim to a) address model selection and relative performance risk, whilst b) increasing the probability of outperforming cap-weighted indices (Amenc et al., 2012).

#### 2.1.3. Heuristic strategies – equal and fundamental weighting

On the other hand, heuristic strategies embody the concepts of equal weighting and fundamental weighting. In the equal weighting framework, where the weight of each company is set to 1/N, there are disadvantageous consequences requiring consideration. For instance, cap-weighting benefits, such as liquidity, investment capacity, performance characteristics and being representative of the average investor in the equity market, are not conserved when equally weighting. Moreover, this indexing design is highly sensitive to the number of constituents included. The latter point is exemplified by looking at the difference of the S&P 500 and the Russell 1000 and their corresponding equally weighted benchmarks. In this regard, there exists a minimal return difference between the two cap-weighted indices. However, when all stocks have the same loading (1/500 for the S&P and 1/1000 for the Russell) the performance difference between the two is considerably amplified. In other words, when two diverse benchmarks are cap-weighted, their risk-return characteristics are quite similar, but when they are equally weighted, the difference is more pronounced. Lastly, there is also a logical inconsistency with this index design since in an index formed of 500 stocks, the smallest company has the same importance as the largest, whereas the 501st has a zero weight.

In the case of fundamental weighting, Arnott et al. (2005) attempt to reinvent indexing by focusing on a simple strategy that could over-perform, in mean-variance terms, that based on market cap. Four accounting values, namely sales, cash flow, book value and dividends, taken in relative terms to the remaining companies, equally contribute to set the weight of each stock in the index. Their hypothesis, supported by the results in the paper, that the market is noisy in the short run and efficient in the long run. The latter predicts that fundamental indexing will perform better over longer horizons. Many practitioners, such as ETFs issuers, follow the 'fundamental' spirit of Arnott and modify it by only considering dividends as weighting factor. This approach is supported by the intrinsic nature of dividends as a fundamental measure not affected by creative accounting nor different accounting standards, and is therefore objective and transparent (Siegel, 2006). Further studies have supported alternative strategies of fundamental indexing using smoothed cap weights by setting stock loadings to be equal to the median of the last 12 to 120 months capitalisation weight (Chen et al., 2007) and collared weighting by assigning cap weights unless they diverge significantly from fundamentals (Arya & Kaplan, 2006).

### 2.2. Capitalisation vs market value indifferent weighting - the theoretical debate

Following the empirical evidence in favour of MVI in Arnott et al. (2005), the literature has focused on understanding whether the results were sample-specific or were likely to persist in the future. Therefore, research began to investigate CW and MVI theoretically and gave rise to a debate. The major contributors supporting the new approaches, such as Treynor (2005), Hsu (2006), Arnott and Hsu (2008), all argue that CW suffers from a performance drag caused by the index design that gives more weight to overvalued stocks and less weight to those which are undervalued. In other words, they assume that market prices are not efficient, i.e. they are equal to fair value plus noise. Yet, the pricing errors of over and undervalued stocks will counterbalance, making its expected value equal to zero in the cross section. This means that arbitrageurs cannot exploit the inefficiencies directly by implementing stock-picking strategies. Furthermore, a common denominator of these studies is the realistic assumption that investors do not need to know the true value of a company in order to benefit by investing following this style.

Mathematically, the theoretical supremacy of MVI can be traced to the covariance of weights with market prices being equal to zero, whereas for CW they are positive. Equal weighting (EW), for instance, will invest in the same number of overpriced and underpriced stocks, assuming that pricing errors are *iid* (independently and identically distributed). In magnitude or money terms, the two portions will tend to be equal, as opposed to CW, which places higher bets on overvalued companies and lower bets on those that are undervalued. A direct consequence of this portfolio construction that invests the same proportion in small and large cap stocks will therefore be a small-cap market bias in comparison with CW. EW and MVI strategies will hence suffer from a higher sensitivity to this risk factor. In summary, weighting schemes that assign loadings to companies randomly with respect to market mispricing will buy more fair value and should therefore outperform CW. This is the case even without reversion to fair values (Treynor, 2005). Should reversion to true value occur, the positive gains relative to CW would be even higher.

The most important opposition to MVI methodologies is perhaps due to Perold (2007). He states that CW does not inherently lead to a performance drag and that the expected return of this strategy is identical to that of an equally weighted one. The core of the problem, in his view, is that MVI rests on fair value and by keeping it constant, MVI supporters build the market price distribution around it by using the noise probability distribution. He argues that, implicitly, MVI advocates make the unrealistic assumption that stockholders do know fair value. In fact, they only observe market prices and therefore can use the error distribution around this figure. Perold (2007) also claims that since price noise is uncorrelated with fair values it is also uncorrelated with market values, and thus the true value distribution around the observed market price is just the same as the market price distribution around fair value. For this reason, he believes that market cap weighting does not suffer from an a priori downward performance bias. A year later, Jun and Malkiel (2008) presented research opposed to fundamental indexing approaches by characterising them as active strategies that do not produce a positive alpha since their excess returns are explained by the Fama-French factors. Tabner (2012) also favours the capitalisation approach over the equally weighted approach, with the former being more robust in periods of negative shocks due to the lower than average covariance of the largest index members and exhibiting better returns and lower systematic risk.

In summary, on the one hand, MVI supporters argue that a CW strategy would invest more in overpriced companies and less in underpriced ones, which implies that such a portfolio construction is not theoretically optimal. On the other hand, CW followers claim that one would have to know fair values in order to implement an MVI scheme. However, as true values are not observable, CW portfolios cannot be *ex-ante* outperformed. Moreover, another of CW supporters' arguments is that to discriminate against CW requires an additional unrealistic assumption – namely that larger companies are more likely to be overvalued and vice versa, i.e. that there exists a positive correlation between market value and pricing error. Nevertheless, this assumption is never expressed in any of the alternative strategies reviewed in this work.

An attempt to reconcile the two factions on MVI was made by Treynor (2008) and Kaplan (2008). The former suggests that two different and mutually exclusive assumptions lead to opposing conclusions on performance drag. Specifically, CW assumes that the covariance between market price and noise is zero, whereas MVI proponents' theory builds upon a zero covariance between fair value and pricing error. Mathematically, the latter defines the boundaries within which CW performs better than fundamental indexation. When the correlation between fundamental value and fair value is higher than the correlation between market price and fair value, MVI benefits from higher expected returns.

### *2.3. The empirical evidence*

Different from the theoretical viewpoint, the empirical literature on MVI is more homogeneous in its findings and elects MVI as a better indexation methodology over CW. Numerous studies have shown that cap weighted indices are often outperformed in absolute terms as well as in risk adjusted terms. For instance, Arnott et al. (2005) posit that, over a 43 year span, 'Main Street' metrics (fundamentals) applied to the top thousand US stocks benefit from an annual over performance of almost 2% compared to a 'Wall Street' size measure. The CAPM alpha is also found to be positive and statistically significant. Along these lines, Chow et al. (2011) test a variety of alternative indexing strategies including those reported in Section 2 above and not only do they find CW constantly delivers inferior returns, but also that heuristic designs outperform mean variance optimizers. Nonetheless, the superior returns are no longer significant once they are adjusted using the Carhart 4-factor model. These findings help to shed light on performance attribution: it is indeed found that alternative schemes are exposed to the value and size factors, and most importantly, that performances are driven by the larger bets placed on these known risk factors.

Additional explanations have been offered by Branch and Cai (2010). By contemporaneously testing fundamental metrics and cap weighting transformations (squared and higher roots of cap weight, equal weights, which behaves like an extreme root, and exponentials), they find that: a) fundamentals mostly outperformed, b) the square of CW underperformed and c) the roots all outpaced their CW counterpart. Most interestingly, the finding reported that the higher the root, the larger the superior return delivered with equal weighing being the overall winner. From their results, it can be inferred that when CW are exaggerated ($cap^2$), performances deteriorate, whereas when the differences in weights are smoothed out (roots and equal weights), returns are increased. In a more recent study by Amenc, Goltz, and Le Sourd (2009), the performance of market-weighted indices was compared to a set of characteristics-based indices in the US market, showing that there were no significant abnormal returns after adjusting for value tilts.

Empirical analysis subsequent to Arnott et al. (2005) has confirmed that fundamental indexation applied to equity indices produces superior returns in Eurozone countries (Hemminki & Puttonen, 2008), Australia (Mar, Bird, Casavecchia, & Yeung, 2009), and Germany (Mihm & Locarek-Junge, 2010). Furthermore, Walkshäusl and Lobe (2010), investigate the performance of global and 50-country specific fundamentally weighted portfolios providing evidence of outperforming global fundamental indices but not country-specific indices. Finally, there is also supporting evidence in favour of fundamental weighting when companies are replaced by entire nations (country benchmarks and ETFs) to form investment portfolios (Estrada, 2008).

Generally, empirical studies are unanimous that cap-weighted indices are not the best performers either in absolute terms or on a mean-variance basis. Furthermore, the CAPM alphas of fundamentally constructed indices are in most cases positive and statistically significant. However, when risk factor models (Fama and French 3-factor model or Carhart 4-factor model) are implemented, alphas are found to be either negative or no longer significant. It can be inferred that the drivers of the superior performances are therefore value and size tilts of these alternative portfolios.

Overall, it can be argued that the existing literature on alternative indexation strategies adds more to the portfolio theory literature than to the indexation one per se. Yet, ever since practitioners started using cap-weighted indices as investment benchmarks and market portfolio proxies, the line dividing these two topics has grown thinner. For this reason, the purpose of the present study is to fill a gap in the literature investigating market value indifferent indexing in the UK economy using a sample that includes what has been described as a once in 50-year event and compared to the 1929 Great Depression, i.e. the 2008 Global Financial Crisis.

## 3. Data collection and index construction

### *3.1. Investment universe construction*

The investment universe comprises all FTSE All-Share Index constituents from January 1989 until September 2014, including financial companies: Banks, Investment Trusts and Real Estate Investment Trusts (REITs). The sample of 16,716 firm-years includes both dead and live companies and, thus does not suffer from survivorship bias. Both the FTSE All-Share Index and the FTSE 100 index are capitalisation-weighted indices.[7] Members' data from January 1989 to December 1995 are obtained from annual reports of constituents, name changes, inclusions and deletions recorded in the *Journal of the Institute of Actuaries* (for values from 1989 to 1993) and the *British Actuarial Journal* (for values from 1994 and 1995).[8] For January 1996 and September 2014, monthly FTSE All-share components are taken from Thompson Datastream.[9] Individual industry memberships for each firm are retrieved from the four-digit Industry Classification Benchmark (ICB) Subsector code and no sectors are excluded a priori.

[7] The methodology omits stocks listed on the AIM (Alternative Investment Market) as the different listing and regulatory requirements (London Stock Exchange, 2010) would make the combined universe heterogeneous. FTSE All-Share Index firms have to satisfy liquidity and size requirements and represent 98% of the total UK's market capitalisation (FTSE, 2015a). This empirical study is therefore careful in maintaining the investment universe constant to preserve comparability.

[8] See www.actuaries.org.uk.

[9] We are grateful to Chris Godfrey for combining the FTSE All-share constituents from 1989 with their respective Industry Classification Benchmark (ICB) Subsector codes.

### 3.2. Security prices and accounting data

Daily Securities prices and annual accounting data[10] (fundamentals) of the FTSE All-Share Index's selected constituents are provided by Compustat Global via Wharton Research Data Services (WRDS). In mathematical and mnemonic terms, market capitalisations for company $i$ at time $t$ are computed as follows[11]:

$$Market\ Cap_{i,t} = \frac{Number\ of\ shares\ in\ issue_{i,t} \times Daily\ closing\ price_{i,t}}{1,000,000} \tag{1}$$

The stocks' individual daily total return factors are calculated taking into account stock splits and dividends as:

$$TR_{i,t} = \frac{Daily\ closing\ price_{i,t} \times Daily\ total\ return\ factor_{i,t}}{Cumulative\ adjustment\ factor\ (issue)\ ex{-}date_{i,t}} \tag{2}$$

This implies that companies' daily returns are defined as the proportional increases between two consecutive daily total return factors, in mnemonic terms:

$$return_{i,t} = \frac{TR_t}{TR_{t-1}} - 1 \tag{3}$$

In order to compare like with like, in rare occurrences where fiscal years are longer or shorter than 12 months, figures from the income statement and cash flow reports are normalised to 12-month equivalents:

$$Accounting\ value_{i,t} = \frac{Reported\ accounting\ value_{i,t}}{Reported\ fiscal\ year\ length\ in\ months_{i,t}} \times 12 \tag{4}$$

After having created a homogeneous and comparable playing field across all firm-years, the accounting metrics not directly available from Compustat Global were computed as follows[12]:

$$Equity\ book\ value_{i,t} = Total\ common\ equity_{i,t} + Deferred\ taxes\ and\ investment\ tax\ credit_{i,t} - Total\ preferred\ equity_{i,t} \tag{5}$$

$$\begin{aligned} Cashflow_{i,t} = {} & (Earnings\ per\ share\ excluding\ extra\ item_{i,t} \times Number\ of\ shares\ in\ issue_{i,t}) + Cashflow\ relevant\ depreciation_{i,t} \\ & + Cashflow\ relevant\ deferred\ taxes_{i,t} \end{aligned} \tag{6}$$

$$Dividend\ coverage_{i,t} = \frac{(Earnings\ per\ share\ excluding\ extra\ item_{i,t} \times Number\ of\ shares\ in\ issue_{i,t})}{Total\ dividends_{i,t.}} \tag{7}$$

$$Dividend\ payout_{i,t} = \frac{Total\ dividends_{i,t}}{(Earnings\ per\ share\ excluding\ extra\ item_{i,t} \times Number\ of\ shares\ in\ issue_{i,t})} \tag{8}$$

### 3.3. Index construction

We aim to eliminate the *ex-ante* inefficiency of cap weighting indices by constructing indices based on accounting metrics and to create superior indices compared to the FTSE 100, the chosen benchmark. The FTSE 100 constituents are picked from the FTSE All-Share universe based on certain requirements, essentially their market capitalisation. Our methodology creates an analogous subsection of the same universe but uses different criteria not limited to market capitalisation, to produce a variety of indices comparable to the FTSE 100.[13] All FTSE All-Share components are ranked by each of the following fundamentals and the top 100 for these measures is selected and then the following respective indices are formed:[14] book equity value, cash flow, sales, dividends, dividend pay-out ratio, dividend coverage ratio, EBITDA. The metrics are then combined, by taking arithmetic averages, and two additional indices are formed, after having re-ranked all companies by these composite accounting figures. The Composite Income index is composed of Sales, EBITDA and Dividends; lastly, the Composite Dividend index comprises Dividends, Dividend Coverage and Dividend Pay Out ratios.

Different from the existing literature, this study builds indices around accounting figures from the income statement and the statement of cash flows, disregarding the balance sheet. This is intended to reduce the exposure to standard risk factors (size, value and market risk) and in particular to avoid a book-value strategy construction. The Composite Income objective is to blend three intuitive and representative metrics from different sections of the income statement: the two 'extremities' (in terms of where the items appear on the statement), sales and dividends, and a 'middle' one, the EBITDA. Instinctively, such measures can, unlike that proposed by Arnott et al. (2005), guarantee a balance between more and less profitable sectors and between companies that issue dividends and those who do not. On the other hand, the intuition behind the Composite Dividend approach is to rely on this most objective, transparent and non-manipulable accounting figure. Yet, as dividend amounts are discretionary and often used by managers as a means of communication with the markets, the combination with nondiscretionary dimensions, namely dividend coverage and

[10] As annual reports are unrestated they are favoured over quarterly ones.

[11] In daily returns calculations, share issues marked as 'common stock' or 'Mutual or investment trust fund' are used. Year-end market capitalisations and daily returns are computed, respectively, with the latest available trading information for each year and daily closing prices.

[12] Eqs. (5) and (6) are in accordance with the definitions reported on Ken French's website. See mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library/variable_definitions.html.

[13] Thus, index reconstruction goes beyond simply changing the benchmark constituents' weights, as this would imply having a portfolio of companies characterised by a large market cap and a high metric figure, thereby excluding small cap firms with eligible accounting data.

[14] By computing 5-year trailing averages of cash flow, sales, dividends, dividend pay-out ratio, dividend coverage ratio and EBITDA, the volatility of the metrics, and consequently the portfolio turnover, are reduced. Where the sample period available for a particular company was less than five years, the average was calculated on the available figures.

pay-out ratios, aid in constructing a consistent index. In summary, two distinct indices are formed and analysed throughout this study, which we term 'Composite Income' and 'Composite Dividend'.

Firms' individual portfolio weights are simply computed as the proportion of a metric figure compared to the sum of that metric across the filtered top 100 companies. In general terms, this translates mathematically into:

$$W_{Metric,i,t} = \frac{Metric_{i,t}}{\sum_{i=1}^{100} Metric_{i,t}} \tag{9}$$

Eq. (9) holds for all the indices constructed and assures that the sum of the portfolio constituents' weights is always unity. None of the index strategies proposed above allows for short selling and thus, where accounting values happened to be negative, the observation was excluded.[15] This does not, however, mean that in case a company had negative cash flow, for example, it could not be included in another index. Moreover, no minimum or maximum percentage position constraints are set in the construction process for two reasons. First, taking this step would mean a definitive trespass across the active strategy boundary. Second, the methodology lets the accounting figures "speak for themselves", which implies a fairer representation of the underlying economy.

### 3.4. Index rebalancing and the matching of security prices with fundamentals

In the indexing strategy literature, the rebalancing frequency is conventionally one year since higher frequencies do not deliver a large enough performance increase to justify the greater turnover. The indices proposed here are no exceptions, also because the accounting data used are extracted from annual reports. Yet there is less agreement in scholarly research regarding the rebalancing date. Often December, the last day of the calendar year,[16] is chosen without any explicit rationale. Instead, this work intends to make a more informed and justified decision on the rebalancing date. In the sample studied, December is not the fiscal year end for 54% of companies and almost 30% of firms' years end between January and March, computed by combined firm-months. The elected rebalancing date is therefore the last trading day of September.[17,18]

Since a whole year of accounting data is required to calculate the constituents and their relative importance, the initial investment date is the 1st October 1990[19] whereas the final one is the 30th September 2014, precisely one year after the latest possible rebalancing date given the availability of fundamentals on the 30th September 2013. Thus the empirical study effectively spans a 24-year sample.

### 3.5. Benchmarks

For comparability and benchmarking purposes, two further indices are also constructed: a composite Arnott index[20] (or Composite) which combines Book Value, Cash Flow, Sales and Dividends and a cap-weighted index. For the latter, the market capitalization, as calculated in eq. (1), is treated as any other fundamental measure, including the rebalancing frequency and date. The drivers of the slight discrepancies with the FTSE 100 are perhaps the longer rebalancing period of the custom build cap-weighted index and the absence of liquidity and size constraints compared to the FTSE 100.[21] Overall, notwithstanding the different stock selection rules, discrepancies between the UK index and the custom build benchmark are not expected to bias the findings.

### 3.6. CAPM, Fama-French and Carhart regressions

To offer a deeper insight into the indices returns, multiple regressions are run on daily returns. In particular, portfolio returns are regressed on the CAPM, the Fama-French three-factor model (FF3) and the Carhart 4-factor model. Following Fama and French (2012), country specific factors are favoured over US factors as they ought to provide a superior explanation of the returns' time-series variations.[22] The market proxy for these UK factors is the FTSE All-share index. Three month UK Treasury Bill prices obtained from Thomson Reuters Datastream are employed as risk free rate proxies. The Fama-French 3-factor and Carhart 4-factor models are presented below:

$$r_{it} - r_{ft} = a_i + b_{1i}(r_{mt} - r_{ft}) + b_{2i}SMB_t + b_{3i}HML_t + \varepsilon_{it} \tag{10}$$

$$r_{it} - r_{ft} = a_i + b_{1i}(r_{mt} - r_{ft}) + b_{2i}SMB_t + b_{3i}HML_t + b_{4i}UMD_t + \varepsilon_{it} \tag{11}$$

where $r_{it}$ is the return of portfolio *i*, $r_{mt}$ is the market portfolio, $r_{ft}$ is the risk free asset, and $b_{1i}$, $b_{2i}$, $b_{3i}$ and $b_{4i}$ are the sensitivities of portfolio *i* excess returns to the market risk premium, the size (*SMB*), book-to-market (*HML*) and winners minus losers (*UMD*) factor premiums, respectively.

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15 Unreported figures show that the results do not change qualitatively if observations are set to zero rather than being excluded.

16 See, for example, Chow et al. (2011) and Estrada (2008).

17 Adopting the last trading day of the calendar year methodology would imply matching returns with a sizable portion of accounting data at least 9 months out of date. Alternatively, March would be a better rebalancing month, as almost ¾ of fundamental figures would be, at most, 4 months old. Further, to ensure that the accounting data inputted in computing indices' weights is formally announced and made available to the public, a 6-month lag is allowed, thus, postponing the elected rebalancing date to the last trading day of September. Avoiding rebalancing at the end of December also circumvents having to make large trades during the holiday period when traded volumes tend to be very low.

18 The matching procedure between returns and fundamentals described above has a consequence worth noting: the implied minimum "age" of accounting information contributing to portfolio weights formation is six months, whilst the maximum is just over 900 days. The latter case occurs in the rare circumstance when a company's fiscal year ends on April 30th, of year $t-1$, and the portfolio is not rebalanced until 30th September, of year $t+1$.

19 The chosen start date is based purely on data availability. In Section 5 we also perform a battery of robustness tests to show that our findings are not sample dependent nor driven by specific sub-periods.

20 This index is included in order to demonstrate the empirical results of applying the Arnott et al. (2005) construction methodology in the UK and could also be seen as a market value indifferent index benchmark. In a similar vein to our methodology, the Arnott index selects components by ranking companies based on Book Value, Cash Flow, Sales and Dividends, and then equally weighs the four metrics to create the Composite portfolio. Book value and cash flow are included in the study solely to replicate Arnott et al. (2005) but are not included in the indices proposed here.

21 For more details on liquidity and size tests and other possible sources of differences see 'Ground Rules for the FTSE UK Index Series' 2015b.

22 The Fama-French factors and momentum factor were downloaded from the Exeter Business school website. See, http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/ for the factors figures and Gregory, Tharyan, and Christidis (2013) for the construction methodology.

**Table 1**
Time-aggregated weights statistics across all years.

| Index | Maximum | Minimum | Percentiles | |
|---|---|---|---|---|
| | | | 5 | 95 |
| Cap | 10.69% | 0.16% | 0.19% | 3.74% |
| Equal Weight | 1.00% | 1.00% | 1.00% | 1.00% |
| Composite Arnott | 19.05% | 0.11% | 0.15% | 3.20% |
| Composite Income | 17.11% | 0.09% | 0.14% | 3.32% |
| Composite Dividend | 41.45% | 0.16% | 0.22% | 3.65% |

Time-aggregated summary statistics of the constituents' weights for each of the constructed indices over the entire 24-year sample including the maximum and minimum weights and the 5th and 95th percentiles.

## 4. Results

A detailed analysis of the results is presented in this section. In summary, the main findings suggest that the newly proposed fundamental indices are superior to their cap- and equal-weight counterparts. Their achieved annual excess returns range from 2-5%-3.5% with a similar or lower volatility, whilst the resemblance of these indices with the FTSE 100 in terms of total market capitalisation and constituent members, ensures similar levels of stock diversification and liquidity, when rebalancing the portfolio.

### 4.1. Weight characteristics

Table 1 shows time-aggregated summary statistics of the constituents' weights for each of the constructed indices over the 24-year sample. The weights vary over time buy by definition, the mean weight is 1% across all years and portfolios. Maximum weights vary from 10.69% of the reference, to a 41.45% in the Composite Dividend index. This 'extreme' weight was assigned in 1996 to National Grid. The company did extremely well afterwards and, in fact, the Composite Dividend index gained around 50% in 12 months whilst the Composite Arnott rose by 20%, and the Composite Income and the FTSE 100 TR by 30%. Large weights in a single stock are not encountered to the same degree in the Composites and constitute a disadvantage for single characteristic-based portfolios from the perspectives of risk concentration, diversification and transaction costs, due to the high price impact. Reassuringly, however, weights larger than 20% only have a 0.2% frequency in our sample. Furthermore, this phenomenon has obvious but lesser repercussions for the minimum weights, which are indeed considerably lower in the Composite Arnott and Income cases. Unreported figures show that by averaging metrics, i.e. by forming Composite indices, minimum weights are larger thus ensuring greater investability. Any constraints on the weights are intentionally not considered in order to keep the construction steps as simple as possible and to study the behaviour of unrestricted accounting based indices.

The 5th and 95th percentiles are included because 'extreme' weights could be rare occurrences, only affecting a single company during one particular year. Indeed, by removing the 5% tails from the weights distribution in each index, figures are considerably more clustered. This indicates how seemingly unreasonable portfolio proportions (e.g. the Composite Dividend maximum weight) are narrowly confined instances over the 24-year time span.

For purely benchmark purposes, we also construct and analyse an equally weighted index, which we rebalance annually as for all other indices. In practice, such indices are not very often used as investment portfolios since they require constant rebalancing. This is reflected in the high turnover costs shown in Table 4. *Ex ante*, we would expect the Equal Weight index, being market-value-indifferent, to perform better than the Cap Weighted counterpart. All empirical tests we perform are consistent with our expectations. Indeed, overall the Equal Weight index delivers improved performances over the FTSE 100, but fails to outperform our strategies.

### 4.2. Return and performance characteristics

Table 2 summarises numerically and Fig. 1 depicts graphically the characteristics of the portfolio index returns. At a macro level, index returns are visually similar, showing volatility clustering around 2001 (the Dot-Com crisis), 2008 (the subprime bubble), and 2011 (the sovereign debt crisis), with the global financial crisis being the most prominent. The daily average return only varies by 0.01%, from 0.04% to 0.05%. Daily standard deviations diverge to a slightly greater extent with the Composite Dividend being the smallest and Composite Income being the highest. Remarkably, the benchmark returns (both Cap and Composite Arnott) are outperformed by all proposed indices. In terms of volatility, the Composite Dividend performs notably better than the references whilst the Composite Income and Arnott achieve similar figures. Modest returns differences, and to a smaller extent standard deviations discrepancies, are amplified in annualised equivalents, as Table 3 depicts. The minimum figures give insight into the indices' individual downside risk levels. Numbers indicate that the negative extreme daily return is higher than the benchmarks only in the Composite Dividend case. Yet, the scenario changes when moving towards the centre of the distribution by 5% where all Composites have higher fifth percentile returns. The fact that maximum and minimum daily returns of the Composite Dividend index are, in absolute value, the lowest among all

**Table 2**
Daily portfolio returns statistics (1st October 1990–30th September 2014).

| Index | Mean | Standard deviation | Maximum | Minimum | Percentile | | Skewness | Excess kurtosis |
|---|---|---|---|---|---|---|---|---|
| | | | | | 5 | 95 | | |
| FTSE 100 TR | 0.04% | 1.13% | 9.84% | −8.85% | −1.69% | 1.72% | 0.01 | 6.31 |
| Cap | 0.04% | 1.15% | 10.31% | −9.04% | −1.68% | 1.74% | 0.12 | 7.49 |
| Equal Weight | 0.04% | 1.13% | 9.99% | −8.52% | −1.67% | 1.72% | 0.06 | 7.06 |
| Composite Arnott | 0.04% | 1.15% | 10.57% | −9.57% | −1.65% | 1.70% | 0.19 | 8.63 |
| Composite Income | 0.05% | 1.16% | 10.72% | −9.78% | −1.68% | 1.72% | 0.19 | 8.52 |
| Composite Dividend | 0.05% | 0.98% | 8.53% | −7.97% | −1.44% | 1.50% | 0.05 | 7.29 |

This table reports the average, standard deviation, maximum, minimum, 5th and 95th percentiles, skewness and kurtosis of the returns on each of the constructed index over the entire sample period.

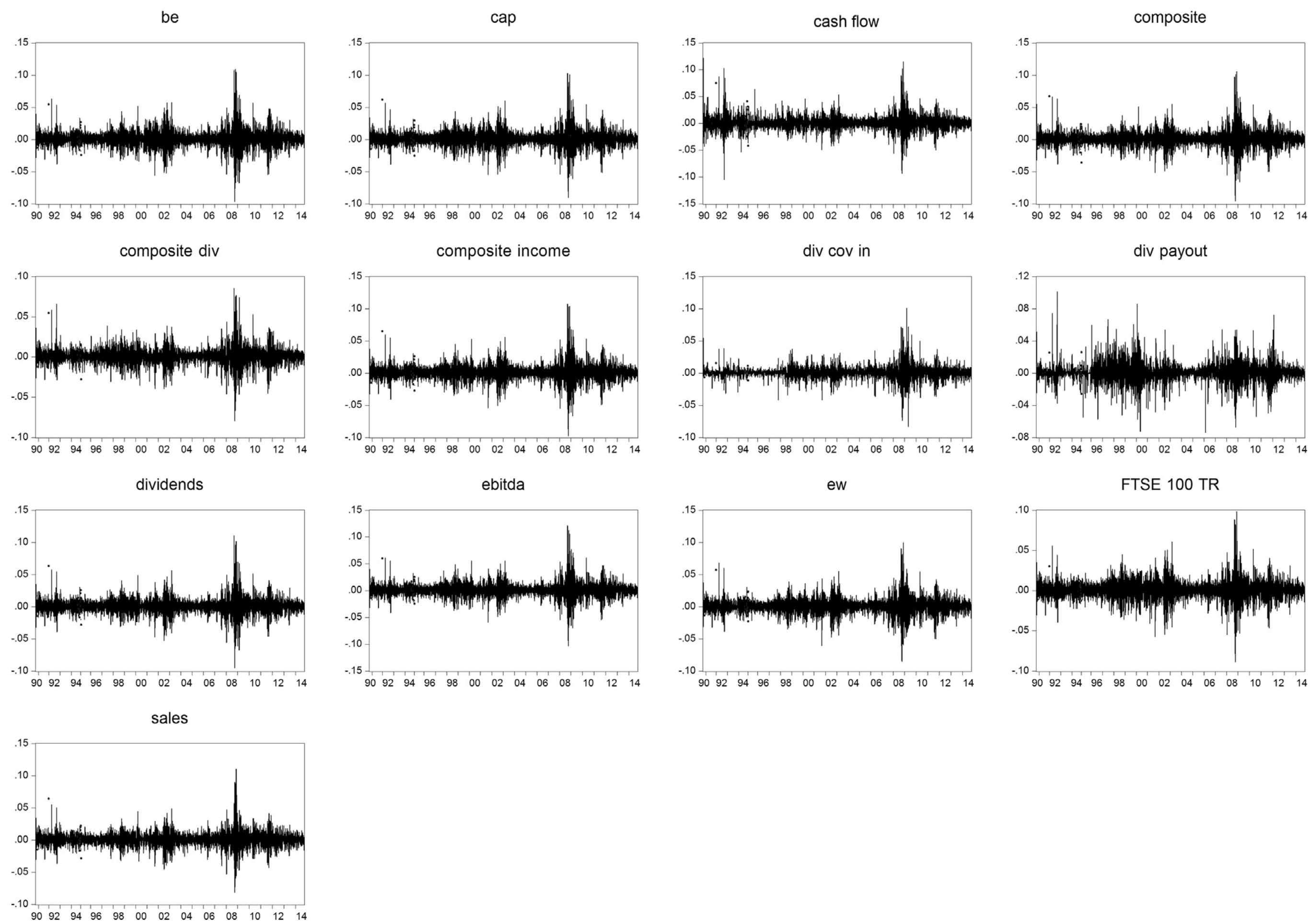

Fig. 1. Daily returns plots (1st October 1990–30th September 2014).

indices, also when winsorised at 95% indicates that actually the concentration risk of this index is well managed by our methodology. This is consistent with the excess kurtosis figures that show 'slimmer' tails in the reference distributions. Lastly, although skewness is positive in all instances, the FTSE 100 is the closest to a normal distribution, followed by the Dividend coverage and Composite Dividend rules. Overall, the proposed indices are characterised by higher returns and more positive skewness compared to the benchmarks.

The outperformance of the Composite Dividend index may be attributed to the decrease of the risk-free interest rate during the sample period, which dropped from 10% to circa 1%. This is likely to be important for two reasons; first, as interest rates decline, investors seeking income will find dividend paying stocks increasingly attractive relative to other yield bearing assets such as cash and bonds, inflating the price of the dividend paying stocks relative to the non-dividend payers. Consequently, this would enhance the total return of the dividend payers and dividend-weighted indices; second, the cost of borrowing, including borrowing to pay dividends has declined. As companies that pay dividends have stable cash flows that facilitate borrowing, it is likely that dividend paying stocks have benefited more from the lower cost of borrowing than the non-dividend paying stocks (Armitage, 2012).

Table 3 illustrates standard portfolio performance measures. Assuming an initial investment of £1 on 1st October 1990 finishing on 30th September 2014, one can see the wealth accumulated by each of the indices. All accounting based portfolios have generated more wealth for every pound invested compared to the cap weighted indices. The Composite Dividend approach even doubled the final wealth compared to the London Stock Exchange index. In annual terms, the Composite Income and Dividend approaches generated 10.94% and 12.14% average returns respectively whereas the FTSE 100 produced a smaller mean

**Table 3**
Index performance characteristics (1st October 1990–30th September 2014).

| Index | Terminal value of £1 | Annualised compounded returns | Annualised standard deviation | Annualised semi standard deviation | Sharpe ratio | Sortino ratio | CAPM Beta |
|---|---|---|---|---|---|---|---|
| FTSE 100 TR | £7.16 | 8.55% | 17.98% | 12.75% | 0.228 | 0.321 | 1.06 |
| Cap | £8.13 | 9.12% | 18.25% | 12.91% | 0.256 | 0.362 | 1.07 |
| Equal Weight | £9.92 | 10.03% | 17.86% | 12.71% | 0.313 | 0.440 | 1.03 |
| Composite Arnott | £9.74 | 9.95% | 18.22% | 12.83% | 0.302 | 0.429 | 1.04 |
| Composite Income | £12.09 | 10.94% | 18.39% | 12.95% | 0.353 | 0.502 | 1.06 |
| Composite Dividend | £15.65 | 12.14% | 15.58% | 11.11% | 0.494 | 0.693 | 0.84 |

Assuming an investment of £1 on 1st October 1990 until the 30th September 2014, the first column presents the total wealth accrued by each index proposed; the remaining columns present various performance measures on the annualised return performance of the indices.

**Table 4**
Turnover and transaction costs.

| Index | Turnover | Ann comp returns | Net Ann comp returns | Std Dev | Sharpe ratio | Net Sharpe ratio |
|---|---|---|---|---|---|---|
| Cap | 10.17% | 9.12% | 9.03% | 18.25% | 0.256 | 0.251 |
| Equal Weight | 30.34% | 10.03% | 9.75% | 17.86% | 0.313 | 0.297 |
| Composite Arnott | 26.17% | 9.95% | 9.71% | 18.22% | 0.302 | 0.289 |
| Composite Income | 25.08% | 10.94% | 10.71% | 18.39% | 0.353 | 0.341 |
| Composite Dividend | 46.29% | 12.14% | 11.70% | 15.58% | 0.494 | 0.466 |

Table 4 reports arithmetic averages of the yearly turnover over the 24-year sample and summary statistics of the net composite returns after allowing for transactions costs. By construction, a cap-weighted portfolio has the lowest turnover as weights and market capitalisations change simultaneously through time. Following Brooks et al. (2001), we assume a conservative transaction cost of 1.7% on round-trip trade (purchase and sale).

return of 8.55%. In an average year, the Composite indices proposed in this study outperformed their cap-weighted counterparts by 2.39% and 3.59%.

Furthermore, this additional performance does not come at the expense of increased volatility. In fact, the Composite Income index registers a slightly lower standard deviation whilst the Composite Dividend presents an annualised standard deviation, which is 2.4% lower. Naturally, these translate into increased Sharpe ratios (SR) compared with a 0.228 ratio between excess returns and volatility for the FTSE 100, the two proposed Composite portfolios achieve returns of 0.353 and 0.494 per unit of risk, thereby outperforming the Composite Arnott index too. A twofold increase in the SR, also supported by qualitatively similar Sortino ratios, confirms that both Composite indices are better proxies of the optimal portfolio.

### *4.3. Turnover and transaction costs*

In this section, we provide a thorough analysis of the tradability of our proposed indices, by focusing on turnover and transaction costs and we compare our findings with their cap-weighted equivalents. Table 4 helps to draw conclusions as to which of these portfolios is best when evaluated on this basis.

Turnover is computed as the sum of the absolute difference between the final weights of every 'investment' year (October to September) and the initial weights of the following year. Portfolio ending weights result from price returns, i.e. not taking dividends into account. The figures reported in Table 4 are arithmetic averages of the yearly turnover across the 24-year sample. By construction, a cap-weighted portfolio has the lowest turnover as weights and market capitalisations change simultaneously through time. Additions and deletions due to fluctuations in market caps are the main causes of turnover in a price-based index. Instead, for fundamental-based indices, turnover is generated by: i) the purchase of more shares of companies whose market value has decreased more than the reduction of the accounting metrics or whose market value has increased less than the surge of the accounting metrics; and ii) the sale of stocks of those constituents whose share prices have experienced an upsurge larger than the fundamentals and vice versa. In other words, the turnover of the portfolios reflect the stickiness of the underlying metrics relatively to the market price. On the one hand, accounting measures that correlate the least with stock prices will result in indices with higher turnovers as companies will be added, deleted and reweighted more often. On the other hand, fundamentals that display a higher persistence from year to year (relatively to market prices) would translate in portfolios characterised by lower turnovers. The source of the high turnover in the composite Dividend might therefore be to the fact that dividends tend to be sticky in comparison to stock prices as the management engages in dividend smoothing and tends to be reluctant in cutting them.

Following Brooks, Rew, and Ritson (2001), a conservative transaction cost of 1.7% on round trip trade (purchase and sale) is assumed in order to analyse the impact of turnover on the excess returns of the proposed indices.[23] Owing to the higher turnover, the net annual compounded returns and net Sharpe ratios of alternative indices experience a larger abatement. However, the reductions are not sufficient to reverse the outperformance conclusions made earlier based on gross figures. Indeed, the annual excess returns of the Composite Income and dividend approaches over the cap reference are 1.68% and 2.67% (and 1% and 2% over the Composite Arnott index), whilst Sharpe ratios are 36% and 85% greater respectively (and 18% and 61% larger than for the Composite Arnott index).

**Table 5**
Liquidity and diversification measures.

| Index | Cap ratio | Concentration ratio | Herfindahl Div ratio | Entropy Div ratio |
|---|---|---|---|---|
| Cap | 1.00 | 0.45 | 0.97 | 4.05 |
| Equal Weight | 1.00 | 0.10 | 0.99 | 4.37 |
| Composite Arnott | 0.94 | 0.40 | 0.96 | 3.84 |
| Composite Income | 0.94 | 0.39 | 0.96 | 3.87 |
| Composite Dividend | 0.85 | 0.28 | 0.95 | 3.86 |

The relative investment capacity (cap ratio) is computed as the market capitalization of the index over the market cap of the cap-weighted index, i.e. the benchmark. The portion of the total index capitalization that belongs to the top 10 stocks by metric weight in each index measures the Concentration ratio. This metric reflects the trade-off between diversification benefits and transaction costs. The intrinsic diversification of each index is further evaluated with two methods: the Herfindahl index and the entropy measure of concentration (Garrison & Paulson, 1973). The higher the computed figure, the larger the diversification.

### *4.4. Portfolio liquidity and diversification*

Portfolio liquidity and capacity are important aspects to consider when designing indices. In conjunction with diversification measures, Table 5 helps to further evaluate the quality of the two weighting schemes studied.

The relative investment capacity, or cap ratio, of each index is measured as the market capitalization of that index divided by the market capitalization of the cap-weighted index, which constitutes the benchmark. Results indicate that the total capitalisation embraced by the market value indifferent indices is very close to the benchmark. In light of this finding and since both the FTSE 100 and the composite indices constructed in this study use the FTSE All share as the available investment universe, it is expected that almost all of the Composites' constituents are shared with the FTSE 100. In particular, the average overlap between the constituents of the constructed indices and those of the FTSE 100 is approximately 90%. The cap ratios also aid in quantifying the magnitude of the second advantage of cap weighting over the alternative strategies, namely the market clearing.[24] The above findings are re-assuring for investors, since a similar overall capitalisation and component group of stocks to those of the FTSE 100, reflects an analogous liquidity when rebalancing the portfolio. Composite index figures, ranging from 85% to 94% overlap with the FTSE 100 components, are to be contrasted

[23] In the UK, as of 2015, a stamp duty tax of 0.5% is applicable when buying shares, even from abroad, in UK companies listed on the main market (i.e. excluding AIM) if the transaction value is over £1000; when selling shares, no such tax has to be paid. The remaining 1.2% can be broken down into 0.80% bid-ask spread and 0.40% commission costs (twice).

[24] Indeed, a plausible interpretation of the cap ratio is the relative investment capacity or, in other words, how much money can be invested in price indifferent approaches compared to the traditional one.

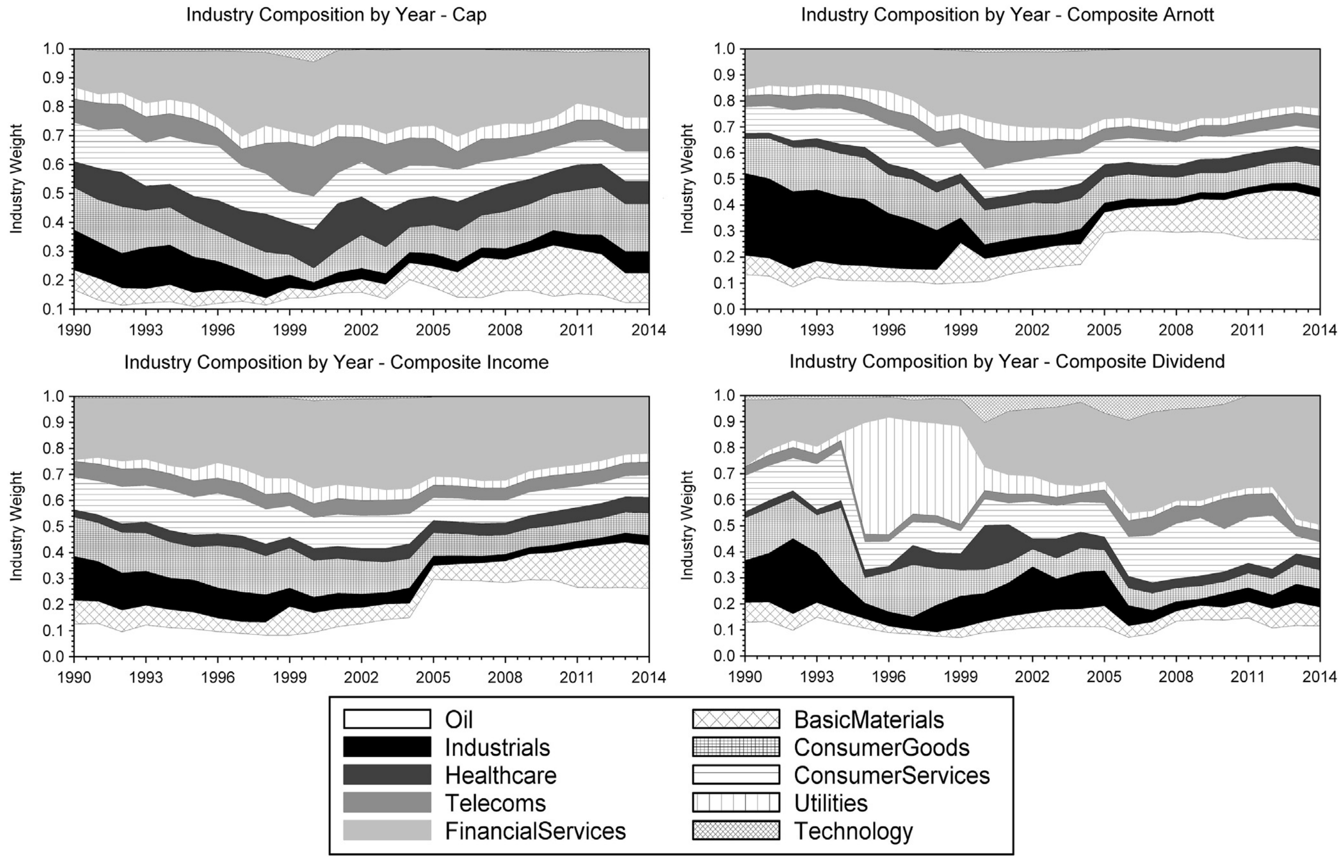


**Fig. 2.** Industry composition by year.

with findings of 2/3 in the US market by Arnott et al. (2005). It can be further concluded that, quantitatively speaking, the market clearing benefit of cap weighting is a minor drawback that shareholders should willingly accept in order to achieve the superior returns that accounting based indices can generate.

The concentration ratio is measured by considering the portion of the total index capitalization that belonged to the top 10 stocks by metric weight in each index, reflecting the trade-off between diversification benefits and transaction costs. All display a cap concentration in the top decile of the index comparable to or lower than the benchmark.[25]

The inherent diversification of the strategies is further gauged by two statistical measures: the Herfindahl index and the entropy measure of concentration suggested by Garrison and Paulson (1973). Although initially proposed as measures of economic concentration, we argue that meaningful results can also be obtained when these statistics are applied to financial portfolios. The larger the calculated value, the higher the index diversification. The formulae used in computing the metrics are the following:

$$H = 1 - \sum_{n=1}^{100} w_n^2 \tag{12}$$

$$E = -C \sum_{n=1}^{100} w_n \ \ln w_n \tag{13}$$

where:

$w_n$ is the weight of the company $n$ in the index and $C$ is an arbitrary scaling constant set to 1.

[25] On the one hand, a lower relative cap amount in top constituents may offer greater diversification benefits, yet on the other hand, it might be more challenging and costly to synthetically replicate a less concentrated portfolio.

Noticeably, Eq. (13) is maximised when $w_n$ is 1/100, i.e. in the case of an equally weighted portfolio. Qualitatively, the results of both diversification measures do not differ and the Composites follow closely behind the cap-weighting scheme under both metrics. In summary, the concentration ratio determines that the alternative portfolios are better diversified in the top 10th percentile, though the inference is reversed when examining the entire index composition.

### *4.5. Industry composition*

Some additional analysis of interest is contained in Fig. 2 by presenting index composition by sector. Notably, the Composite Income index is characterised by the most stable allocations, closely followed by the Composite Arnott. These portfolios fairly represent the gentle transition of the industry composition in the UK economy, captured by the development in accounting measures. In contrast, the reference portfolio reflects the variations in investors' preferences exemplified by the technology and telecoms temporary peaks around 2001. Accordingly, accounting based indices might be used, inter alia, by regulators and investors as superior indicators of the real economy given their ability to dampen the effects of stockholders' sentimentality on index composition.

## 5. Robustness tests

The analysis is focused on the comparison between the two benchmarks considered (Cap and FTSE 100 indices) and the two Composite indices (income and dividend). From a mean variance perspective, the superior Sharpe and Sortino ratios contained in Table 3 indicate the larger returns per unit of risk taken (measured by volatility and semivolatility). The inferences made would not be different if risk was measured by the market beta, since the positive excess returns come with

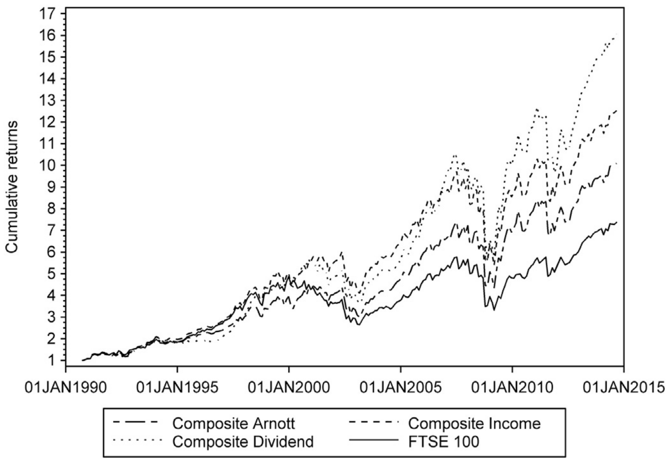


**Fig. 3.** Cumulative returns & benchmark and cumulative growth of £1 (1990–2014).

analogous or lower systematic risk levels. On similar grounds, the lower kurtosis can be interpreted as a lower risk of extreme events and therefore a statistically higher probability of future returns being closer to the reported average returns, i.e. the mean of the distribution.

### 5.1. Cumulative returns

Fig. 3 presents no evidence that long-term performances are dominated by one particular sub-sample period. In fact, the net asset value of the Composite Income and Dividend steadily grew with time, outperforming both the Composite Arnott and, even more so, the FTSE 100. Moreover, the spread between the former two and the latter two broadens through time. Our intuition on the divergence between 'Income' and 'Dividend', depicted from around 2011 until the end of the sample, is the poor performance of fixed income yields and the consequent flight of investors towards high dividend paying stocks.

To overcome any 'starting point' bias, cumulative returns are computed by rolling the initial investment date forward in 6-month steps. The x-axis in Fig. 4 reports the entry date, whilst the y-axis shows the terminal values of £1 for the respective entry dates, i.e. the final points of the index value lines traced in Fig. 3. Note, firstly, how the excess returns over the benchmark diminish for shorter investment horizons, yet in no circumstances do they turn negative. Thus, moving the initial date forward does not lead to qualitatively different performances compared to the results previously presented, consistent with the hypothesis of *ex-ante* inefficiency of cap-weighted indices. Indeed, the ultimate performance is unaffected by market movements as the FTSE 100 loses ground in favour of accounting-based indices because of its very nature. Only time is able to show the efficiency gap between the two conceptually different indexation strategies and hence, from an investment perspective, the proposed indices should be regarded as long-term investments.

In a similar fashion, examining 5-year rolling investment windows relieves any possible 'ending date' bias. Panel A of Fig. 5 still traces the FTSE 100 below all other indices most of the time. Interestingly, the benchmark delivers the relatively best returns in booming times and when bubbles form, for example before 2000, 2008 and 2011. Yet, as crises begun, its performance plummeted. In fact the FTSE 100 is the only index that crossed the £1 dotted line, meaning that only the Composite indices always secured a final investment value, in nominal terms, at least as large as the initial one. Panel B displays even more clearly the superior performance of the Composite Income.

Throughout the sample analysed, in fact, its excess returns over the FTSE 100 have consistently been positive with two exceptions: the strongly bull markets preceding the dot-com and sub-prime crises. Under such circumstances a market price-based approach could be regarded as a momentum strategy that effectively puts increasingly higher bets, owing to the market cap expansion, on stocks that have performed well in the recent past. During strong momentum phases, cap-weighted strategies are, by construction, challenging to outperform as they directly exploit that market feature. Yet only in such market

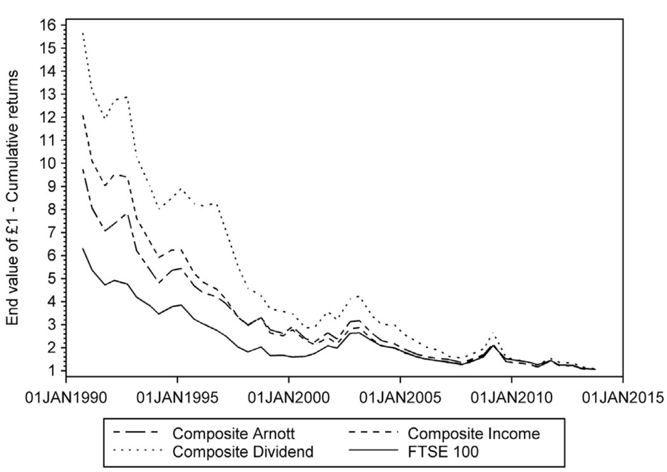


**Fig. 4.** Cumulative returns at 6-month rolling entry date. We calculate cumulative returns by moving the initial investment date forward in 6-month steps to address any 'starting date' bias. The x-axis is the entry date, the y-axis is the terminal value of £1 for the respective entry dates (the investment ending values reported in Fig. 3).

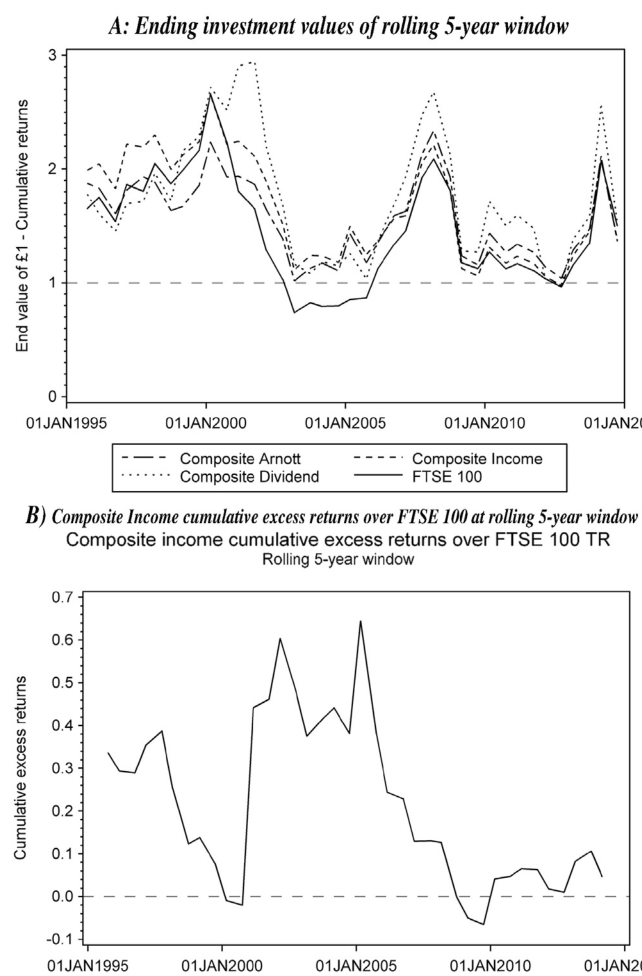


**Fig. 5.** Cumulative returns at rolling 5-year window. Any ending date bias is overcome by looking at 5-year rolling investment windows. Panel A plots the FTSE 100 and accounting based indices. Panel B presents the overperformance of the Composite Income over the Cap.

**Table 6**
Yearly returns.

| Year | FTSE 100 TR | Cap | Equal Weight | Composite Arnott | Composite Income | Composite Dividend | Comp Inc. – FTSE | Comp Div – FTSE |
|---|---|---|---|---|---|---|---|---|
| 1991 | 29.33% | 29.48% | 25.57% | 31.10% | 28.22% | 26.47% | −1.11% | −2.86% |
| 1992 | 9.16% | 9.55% | 4.18% | 4.24% | 8.27% | 0.77% | −0.89% | −8.39% |
| 1993 | 20.93% | 20.10% | 25.15% | 36.73% | 36.14% | 40.89% | 15.21% | 19.95% |
| 1994 | −1.13% | 4.63% | 6.48% | 1.00% | 6.10% | 0.15% | 7.24% | 1.28% |
| 1995 | 28.28% | 28.11% | 28.65% | 22.02% | 29.06% | 9.36% | 0.78% | −18.92% |
| 1996 | 18.91% | 16.13% | 13.54% | 10.26% | 16.73% | 12.64% | −2.18% | −6.27% |
| 1997 | 33.51% | 33.10% | 27.94% | 25.10% | 33.33% | 50.22% | −0.19% | 16.71% |
| 1998 | 6.94% | 7.09% | 10.01% | 8.53% | 10.02% | 29.90% | 3.08% | 22.97% |
| 1999 | 10.94% | 9.13% | 9.33% | 3.31% | 3.31% | 3.60% | −7.64% | −7.35% |
| 2000 | −1.59% | 19.04% | 16.96% | 30.77% | 33.62% | 24.49% | 35.22% | 26.09% |
| 2001 | −15.51% | −21.83% | −22.40% | −7.09% | −2.99% | −10.31% | 12.52% | 5.20% |
| 2002 | −27.36% | −27.65% | −26.60% | −25.35% | −25.02% | −23.36% | 2.35% | 4.00% |
| 2003 | 29.50% | 32.65% | 39.26% | 35.16% | 35.94% | 37.86% | 6.45% | 8.37% |
| 2004 | 10.53% | 10.47% | 14.62% | 15.59% | 14.15% | 11.64% | 3.62% | 1.10% |
| 2005 | 22.37% | 21.46% | 25.63% | 23.48% | 21.35% | 30.78% | −1.02% | 8.41% |
| 2006 | 11.61% | 12.70% | 21.71% | 10.23% | 9.84% | 25.04% | −1.77% | 13.42% |
| 2007 | 8.17% | 7.35% | 0.46% | 9.92% | 7.25% | 4.47% | −0.92% | −3.70% |
| 2008 | −29.00% | −29.21% | −31.58% | −27.99% | −30.78% | −32.93% | −1.78% | −3.93% |
| 2009 | 19.93% | 36.54% | 44.40% | 33.53% | 32.43% | 50.81% | 12.50% | 30.88% |
| 2010 | 10.82% | 14.39% | 18.82% | 12.20% | 11.44% | 15.91% | 0.62% | 5.09% |
| 2011 | −7.03% | −10.11% | −9.58% | −12.46% | −12.26% | −18.67% | −5.23% | −11.65% |
| 2012 | 16.17% | 18.04% | 21.82% | 19.15% | 19.73% | 28.27% | 3.56% | 12.09% |
| 2013 | 17.18% | 16.79% | 19.56% | 13.23% | 14.23% | 22.42% | −2.95% | 5.24% |
| 2014 | 2.36% | 1.39% | 1.36% | 2.92% | 2.47% | 3.80% | 0.11% | 1.44% |

Yearly returns over the 24-year sample. The last two columns present the difference in returns between our two indices and the FTSE 100. Positive (negative) figures indicate a higher (lower) performance delivered by the Composite Income or Dividend indices.

scenarios does the cap weighting return tend to align with the Composite indices. The overall outperformance of the proposed strategy over the FTSE 100 is, however, clearly depicted. This phenomenon is consistent with the short run noise and long run market efficiency hypothesis. To complete the analysis, Tables 6 and 7 present annual and 5-year period returns respectively, providing evidence that the proposed indices produce a continuous over-performance over the entire sample with no year-specific or sub-period effects.

### *5.2. Maximum drawdown*

An additional statistical tool that portfolio managers often quote is the maximum drawdown (DD). Fig. 6, Panel A, plots the percentage maximum DD calculated over a 60-trading day (a quarter) window. As expected, the largest drawdowns occurred during the two crises. For all four indices, the 2008 financial crisis registered the largest DD (of around 30%) over the whole period. At first sight, the maximum drawdown plots are comparatively similar, with perhaps the exception of the Composite Dividend. Panel B, displays the graphs of Panel A combined into a single chart. Starting with the most prominent decline, as anticipated, the Composite Income and Arnott rules record similar figures whilst the Composite Dividend registers a modestly greater fall in value of circa 40% over a quarter. Around the year 2000, three other significant troughs are depicted on the graph; interestingly, in two occurrences the FTSE 100 lost the most ground, with the market value indifferent indices, instead, suffering smaller or similar losses between them. In conclusion, given the high degrees of resemblance, the maximum drawdown does not represent a significantly discriminating metric between cap and accounting weighting schemes.

## 6. Performance attribution

The strongest opponents of accounting based indexation, including Blitz and Swinkels (2008) and Asness (2006), argue that the source of its outperformance over cap weighted portfolios originates from its exposure to Fama-French factors, and in particular to value. Indeed, Arnott et al. (2005), as well as Chow et al. (2011) are unsuccessful in finding positive and significant 3-factor and 4-factor alphas. The following two tables aim to elucidate whether excess earnings persist once daily returns are regressed onto a variety of risk factors, thereby outlining possible performance drivers. The first regression is performed using an intercept, in order to estimate the mean returns. As parameters are added to new regressions, p-values indicate whether the intercepts will remain positive and significantly different from zero. The reported regression alphas are annualised unless otherwise stated.

Panel A of Table 8 shows the average arithmetic returns over the whole sample. Here there exist two noteworthy observations. Firstly, Composite indices display significantly positive mean returns, whereas the FTSE 100 does not. Secondly, the Composite Income and Dividend do better than the sums of their parts. Indeed, unreported results show that the mean alpha computed from their respective components is lower than their actual intercept; the Composite Arnott index fails to accomplish this, however.

Panel B, instead, gives insight into the market risk adjusted returns. In this scenario, the Composite Arnott and the FTSE 100 do not provide

**Table 7**
5-Year multi-period returns.

| Period | FTSE 100 TR | Cap | Equal Weight | Composite Arnott | Composite Income | Composite Dividend | Comp Inc. – FTSE | Comp Div – FTSE |
|---|---|---|---|---|---|---|---|---|
| 1990–1995 | 110.53% | 121.12% | 117.29% | 124.64% | 151.82% | 92.51% | 41.29% | −18.03% |
| 1995–2000 | 82.00% | 110.48% | 102.99% | 98.15% | 130.65% | 182.13% | 48.65% | 100.13% |
| 2000–2005 | 8.46% | 1.53% | 15.34% | 35.33% | 38.53% | 39.38% | 30.07% | 30.92% |
| 2005–2010 | 15.68% | 35.47% | 44.25% | 32.03% | 21.56% | 54.99% | 5.88% | 39.31% |
| 2010–2014 | 30.98% | 27.16% | 34.97% | 22.31% | 23.71% | 31.77% | −7.27% | 0.78% |

5-Year multiperiod returns over the 24-year sample. The last two columns present the difference in returns between the two proposed indices and the FTSE 100. Positive (negative) figures indicate a higher (lower) performance delivered by the Composite Income or Dividend indices.

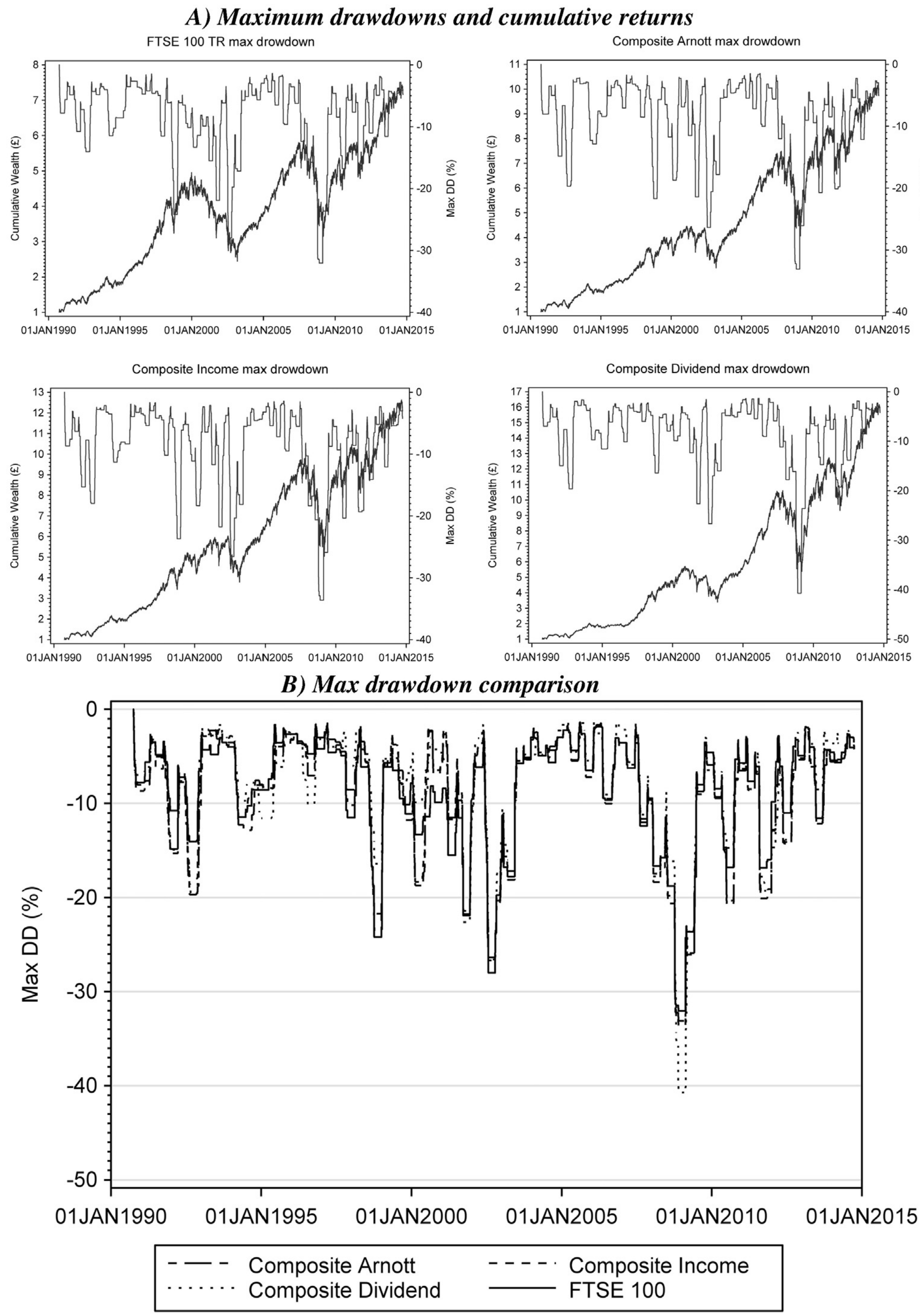


**Fig. 6.** 60-Days max drawdown. Panel A, presents the percentage maximum Drawdown (DD) computed over a 60-trading day window. Panel B, combines DD plots of Panel A in a single chart.

statistically significant alphas. Moreover, the excess returns of the Composite Arnott and Income diminish marginally once market risk is accounted for. On the contrary, the Composite Dividend's superior performance, in relation to the benchmark, grows by almost one hundred basis points from 3.45 pps to 4.40 pps. This implies that market exposure is not the propeller of the excess performance.

The Fama-French 3-factor regressions[26] reported in Table 9, Panel A, indicate that, first and most importantly, the two novel indices (Composite Income and Dividend) succeed where the market value indifferent literature has so far not. Refreshingly, the returns of the two constructed portfolios are positive and significant even when accounting for market (rmrf), value (hml) and size (smb) factors (Fama & French, 1992). Their positive excess returns, displayed in Panel B, are also statistically different from zero net of the Carhart (1997) 4-factor exposure effects. Furthermore, it is worth noting how the intercepts of the Composites change from the simplest regression to the Carhart 4-factor specification. As expected, the alphas generally decrease as more factors are added; the "unexplained" returns show a drastic fall, around 6%, in the CAPM regression, indicating the tie of these portfolios with the whole market. Yet, netting the effects of value, size and even momentum only decreases the intercepts by less than 1% in all instances.

[26] The market proxy in this analysis is the original investment universe, i.e. the FTSE All-share index.

**Table 8**
Regressions on intercept only and CAPM.

| Panel A: regression on intercept only | | Panel B: regression on CAPM | | |
|---|---|---|---|---|
| Index | α | Index | α | rmrf |
| FTSE 100 | 5.13% | FTSE 100 | −0.57% | 1.06*** |
| | 0.166 | | 0.148 | 0.00 |
| Cap | 6.26%* | Cap | 0.17% | 1.07*** |
| | 0.097 | | 0.789 | 0.00 |
| Equal Weight | 7.06%* | Equal Weight | 1.26% | 1.03*** |
| | 0.057 | | 0.214 | 0.00 |
| Composite Arnott | 7.02%* | Composite Arnott | 1.11% | 1.04*** |
| | 0.062 | | 0.304 | 0.00 |
| Composite Income | 7.97%** | Composite Income | 1.98%* | 1.06*** |
| | 0.036 | | 0.057 | 0.00 |
| Composite Dividend | 8.58%*** | Composite Dividend | 3.83%*** | 0.84*** |
| | 0.008 | | 0.006 | 0.00 |

*, **, *** = significant at 10%, 5% and 1% confidence level. Reported regression alphas are annualised. Panel A displays the results (and p-values underneath) of regressions of returns using only an intercept, i.e. the mean returns over the period. Panel B, instead, shows the market risk adjusted returns.

All Composite indices have a positive and significant exposure to the value (hml) factor, whilst the Composite Dividend is also meaningfully exposed to size (smb). Table 9 illustrates that, in contrast with the FTSE 100, which displays negative value and size exposures reflecting its tilt towards large and growth companies, the Composite indices offer a reliable avenue for accessing value and size premia. A second and perhaps less straightforward vindication is found in the noise-in-price literature. Arnott and Hsu (2008) and Arnott, Hsu, Liu, and Markowitz (2014) find that, de facto, any deviations from priced weighted portfolio construction would spontaneously lead to value exposures.

Overall, the above findings display how the proposed accounting based indices benefit from higher Sharpe and Treynor ratios and also exhibit positive and significant Fama-French and Carhart alphas, evidence of better portfolio construction rather than a higher exposure to known risk factors.

## 7. Conclusions

A widespread consensus among financial markets participants is to proxy the mean-variance efficient market portfolio with cap-weighted indices. The entire passive investment industry, including a large fraction of ETFs, base their investment belief on this assumption. However, both theoretically and empirically, the hypothesis does not hold. Although capitalisation weighted indices benefit from a variety of advantages, this study argues and empirically shows that investors can do better if they 'marry' price indifferent strategies such as the proposed Composite Income and Dividend portfolios, in absolute terms and on a risk adjusted basis.

This research fills a gap in the literature by first providing out-of-sample results on the UK market that can be compared with those from the seminal paper by Arnott et al. (2005) paper. We employ a 25-year data sample that spans from 1989 to 2014 and thus includes the 2008 financial turmoil. Two simple, novel index designs are also proposed, both characterised by annual rebalancing and relative portfolio proportions derived from readily available accounting values such as Sales, Dividends and EBITDA. Composites formed by simple arithmetic averages of fundamentals are also tested and found to be preferable over single metrics.

In summary, the results show that annual excess returns ranging from 2.39% for the Composite Income index to 3.59% of the Composite Dividend series are achieved over the sample analysed, experiencing analogous or lower volatility compared to the FTSE 100. Predictably, the resulting Sharpe ratios increased more than twofold in certain cases. The higher turnover, by construction, of deviations from cap weighting implies larger trading fees, but nonetheless the superior performance is robust to the assumed 1.7% transaction cost. At the same time, the similarities of the indices with the FTSE 100 in terms of total market capitalisation and constituent members ensure similar levels of liquidity when rebalancing the portfolio.

It is also found that the Composite Dividend and Income outperformances are robust across time, bull and bear markets and independent of initial and terminal investment dates. Further, owing to the fairer representation of the underlying economy, such indices could find further application in regulatory and investment decision-making. Overall, our findings are not only consistent with those of the market value indifferent literature in that cap weighting can be improved in mean-variance terms, but also present an outperformance of the proposed indices over Arnott et al. (2005).

From a theoretical perspective, these results support noise-in-price models that imply an *ex-ante* underperformance of cap weighting and contribute to backing the hypothesis that the market is noisy in the short run and efficient in the long run. The Composites vividly outperform capitalisation weighting in all other circumstances, which contribute to a two-fold increase in terminal portfolio values. Based on regressions of returns on standard pricing models (CAPM, FF3 and Carhart), the sources of the proposed indices' outperformance are found in the following elements. Firstly, a true ex-ante inefficiency of cap weighting that market value indifferent strategies are able to overcome. Secondly, a greater exposure to risk factors in addition to market, value, size and momentum. Thirdly, as the significant FF three-factor Carhart 4-factor alphas demonstrate, a better portfolio construction. We see no evidence that the findings presented would not be replicated in the future given the long and internally varied sample studied and the factor-adjusted return results. Indeed, the proposed indices could

**Table 9**
Regressions on Fama-French 3-factor and Carhart 4-factor models.

| Panel A: regression on FF 3-factor | | | | | Panel B: regression on Carhart 4-factor | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Index | α | rmrf | smb | hml | Index | α | rmrf | smb | hml | umd |
| FTSE 100 | −0.19% | 1.013*** | −0.142*** | −0.028*** | FTSE 100 | −0.15% | 1.014*** | −0.141*** | −0.028*** | 0.004*** |
| | 0.479 | 0.000 | 0.000 | 0.000 | | 0.569 | 0.000 | 0.000 | 0.000 | 0.003 |
| Cap | 0.37% | 1.029*** | −0.110*** | 0.053*** | Cap | 0.20% | 1.025*** | −0.113*** | 0.053*** | −0.019*** |
| | 0.544 | 0.000 | 0.000 | 0.000 | | 0.739 | 0.000 | 0.000 | 0.000 | 0.000 |
| Equal Weight | 0.76% | 1.058*** | 0.094*** | 0.110*** | Equal Weight | 0.50% | 1.052*** | 0.091*** | 0.111*** | −0.028*** |
| | 0.389 | 0.000 | 0.000 | 0.000 | | 0.553 | 0.000 | 0.000 | 0.000 | 0.000 |
| Comp Arnott | 0.74% | 1.031*** | 0.007 | 0.229*** | Comp Arnott | 0.71% | 1.030*** | 0.007 | 0.229*** | −0.002 |
| | 0.451 | 0.000 | 0.262 | 0.000 | | 0.465 | 0.000 | 0.286 | 0.000 | 0.641 |
| Comp income | 1.67%* | 1.045*** | 0.001 | 0.195*** | Comp income | 1.79%* | 1.048*** | 0.003 | 0.195*** | 0.014*** |
| | 0.082 | 0.000 | 0.882 | 0.000 | | 0.062 | 0.000 | 0.666 | 0.000 | 0.005 |
| Comp Dividend | 3.16%** | 0.908*** | 0.204*** | 0.102*** | Comp Dividend | 3.23%** | 0.910*** | 0.205*** | 0.102*** | 0.008 |
| | 0.017 | 0.000 | 0.000 | 0.000 | | 0.015 | 0.000 | 0.000 | 0.000 | 0.232 |

*, **, *** = significant at 10%, 5% and 1% confidence level. Reported regression alphas are annualised. Panel A reports Fama-French 3-factor regression results whilst Panel B reports Carhart 4-factor regression results.

provide a robust path for enhanced performance and benefit passive investors.

Further research could be pursued in the field of market value indifferent indexation given the strong empirical evidence available throughout a range of markets. Additional applications, such as the regulatory one cited above, are worth exploring in more detail. Equally, analogous empirical tests could be applied to the broader UK indices using more relaxed criteria such as short selling or constraints such as maximum and minimum weights, as well as examining their performance over long bearish periods. Disentangling the possible performance attribution drivers would also further assist researchers in understanding which really contribute to the excess returns.

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