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Executive Summary

Research Proposal

This paper is constructed with the purpose of assessing the performance of a 'Dogs of the Dow' dividend yield strategy in the British stock market in the period 2002 - 2016.

Research Design

Two simulated 'funds' with an initial value of £10,000 were constructed to employ a DoD strategy and a strategy to invest passively in the FTSE 100 benchmark. To construct the DoD portfolios, the following methodology was employed: First, on the first trading day of the year, an equally weighted portfolio consisting of the ten stocks in the FTSE 100 with the highest trailing dividend yield is constructed. Second, after holding the portfolio for one year, the terminal value of the portfolio is determined on the basis of all dividends along with the closing values of the stocks to compute the return. Third, next year, re-allocate 10% of the new total value in each of the ten highest yielding FTSE 100 stocks. Each of the three steps is then repeated annually. Once constructed, all portfolios' performance is assessed using absolute and relative risk measures.

Research Findings

The study shows that the Dow strategy outperforms the FTSE market index in risk-adjusted terms for the sample period. The average (median) excess return of 6.43% (9.37%) also compensates transaction cost, hence the Dow strategy also outperforms in terms of nominal measures. It also finds that relative risk measures such as Sharpe, M2, Treynor and Sortino ratios all favour the DoD portfolio to the benchmark.

Research Limitations

It might be difficult to extend the results into a real world situation. The DoD strategy requires annual rebalancing in which transaction costs are assumed to be a one-way cost of 1%, thus failing to consider the potential asymmetry of costs between past winners and losers among other elements of market microstructure. The impact of taxation is also not incorporated as yet another simplifying assumption, and future studies would need to consider these factors when assessing the performance of the Dow strategy. A longer sample period could be employed to reduce the potential effects of 'data mining', and it would be considered good practice to test the robustness of the results by conducting a sensitivity analysis through alternative starting months. This way, effects of seasonality would be eliminated.

Research Implications

The results suggest that implementing the Dow strategy in the British market could yield abnormal performance. This raises further questions, such as how much of the body of work confirming the DoD's empirical success is as a result of data mining? If not, the absence of investor learning may indicate a challenge to efficient markets. It may also be that considering the research limitations above dramatically change the performance of the strategy.

Research Originality

This paper is the most recent study and has the second longest sample period on the performance of the Dow strategy in the British market. It is also the first paper to use a comprehensive suite of risk measures, as most papers only use one or two measures. Finally, this is the first paper to test the DoD portfolio against various factor models to evaluate significance instead of a simple t-test.

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All code is located in the appendix of this paper, and is also available at:
https://github.com/Jorgencr/Alternative-and-Responsible-Investments

1 Introduction

Investors have always searched for ways to outperform the market, and several investment strategies promising abnormal return have evolved. The 'Dogs of the Dow' (hereafter DoD) is a such strategy that has been the topic for numerous studies since its origination. This study reviews existing literature and examines the performance of the DoD dividend yield investment strategy in the British stock market during the period 2002 - 2016, and thus extending the findings of Filbeck and Visscher (1997) and Brzeszczynski et al. (2008). Previous studies advocate that the 'overreaction' effect could explain the abnormal returns affiliated with the strategy, and this paper provides evidence supporting this theory.

Section 2 presents a review of previous literature on the DoD strategy. The methodology employed is discussed in Section 3, before results and analyses are provided in Section 4. Concluding remarks and recommendations for areas of further study are made in Section 5.

2 The Dogs of the Dow

This paper reconsiders the performance of the contrarian dividend investment strategy named 'Dogs of the Dow' (hereafter denoted DoD). DoD was orinally introduced by Slatter (1988), an analyst writing for *The Wall Street Journal*, and provided a simple, but yet feasible investment strategy for investors: by only constructing investors consisting of the top ten dividend yielding stocks included within the Dow Jones Industrial Averages (DJIA), investors should be capable to outperform the benchmark.

DoD is classified as a value-based investment strategy which, according to Filbeck and Visscher (2003), focuses on stocks with traits like high dividend yields, low price-to-book ratios, low price-to-earnings ratios and low expected growth rates - i.e. value stocks. On the contrary, growth stocks are classified by opposite characteristics. Previous research provides support for the relationship between dividend yields and stock returns[1], while later research has focused more on the 'overreaction' anomaly and its implications for stock selection[2]. The overreaction anomaly explains that stock returns can be partially linked to investors' tendency to overreact when faced with surprises. Investors may overreact negatively to negative suprises (e.g. missing earnings expectations) or overreact positively to positive surprises (e.g. beating expectations), which could in turn lead to the formation of value stocks and growth stocks, respectively. Basu (1977), Sorensen and Williamson (1985) and Harris and Marston (1994) have all documented evidence that long-term value strategies tend to be superior in U.S. markets.

The theory of corporate dividend policy suggests that corporations prioritize a stable dividend policy, even during times of financial distress, to avoid sending misleading signals regarding the company's financial situation (Lintner, 1956; Brav et al., 2005; Skinner and Soltes, 2011).[3] From this, dividend yield can be considered an inverse proxy of popularity that will lead to picking stocks temporarily out of favour (Da Silva, 2001).

[1] See Elton and Gruber (1970); Blume (1980); Christie (1990).

[2] For example Bondt and Thaler (1985).

[3] If a firm decides to slash dividends, it may be taken as a signal of financial distress by investors and thus reduce the value of the company (Karpaviius, 2014; John and Williams, 1985).

As many later have pointed out, there are several easily identifiable advantages to this strategy (Hirschey, 2000):

1. The strategy is easy to adopt for any investors, institutional and individual alike. Investors are only required to compute dividend yield on the first trading day of the year in order to rank the stocks in descending order. The top ten yielding stocks will form the portfolio and are held until the first trading day of the next year. Then, the process is simply repeated annually.
2. By only using dividend yield as the criteria for the portfolio, investors are faced with a simple and quantifiable measure that enforces strict investor discipline.
3. Transaction costs are kept at a significantly low level compared to many other strategies, as re-balancing only happens once a year.
4. The trading strategy is only intended to be employed on 'blue-chip' companies included in a rather large and liquid index. As a result, portfolios will have relatively low turnover as the constituents of the index are supposedly more stable.

2.1 Methodology

Methodology is made up of three steps. First, on the first trading day of the year, construct an equally weighted portfolio consisting of the ten stocks in the FTSE 100 with the highest trailing dividend yield. To compute dividend yield, use the annualized value of the last ordinary dividend payment in the previous year and the closing price on the first business day of the next year.[4] In rare cases when a FTSE 100 stock ceases to trade during the year due to a merger or acquisition, invest the proceeds for the stock in the FTSE 100 total market portfolio until the following year.

Second, after holding the portfolio for one year, determine the total value of the portfolio, including all dividends along with the closing values of the stocks, to compute the return.

Third, re-allocate 10% of the new total value in each of the ten highest yielding FTSE 100 stocks. Stocks which have dropped out of the top ten list are to be sold and replaced. Each of the three steps is then repeated annually.

[4] The dividend amount is multiplied by the number of dividend payments per year, i.e. 2 for semi-annually and 4 for quarterly.

2.2 Literature Review

Table 1: Overview of previous literature on the 'Dogs of the Dow' strategy

#	Author(s)	Published	Time period	Country	DoD strategy (%)	Market return (%)	Over-/under performance (%)
1	Brzeszczynski et al.	2008	1994 - 2007	UK	28.23	6.69	21.54
2	Filbeck and Visscher	1997	1984 - 1994	UK	9.48	11.58	-2.10
3	Gwilym et al.	2005	1980 - 2001	UK	20.63	18.53	2.10
4	Filbeck and Visscher	2003	1987 - 1997	Canada	15.11	8.89	6.22
5	Hirschey	2000	1961 - 1998	US	14.16	12.39	1.77
6	McQueen and Thorley	1999	1973 - 1996	US	20.31	15.80	4.51
7	Slatter	1988	1973 - 1988	US	18.39	10.80	7.59
8	Knowles and Petty	1992	1957 - 1990	US	14.20	10.40	3.80
9	O'Higgins and Downes	1991	1973 - 1991	US	16.61	10.43	6.18
10	McQueen et al.	1997	1946 - 1995	US	16.77	13.71	3.06
11	Domian et al.	1998	1964 - 1997	US	-	-	-
12	Da Silva	2001	1994 - 1999	Argentina	2.32	1.66	0.66
	"	2001	1994 - 1999	Brazil	4.64	8.90	-4.26
	"	2001	1994 - 1999	Chile	4.30	1.21	3.09
	"	2001	1994 - 1999	Colombia	-0.83	-1.39	0.56
	"	2001	1994 - 1999	Mexico	2.91	2.22	0.69
	"	2001	1994 - 1999	Peru	2.70	2.49	0.21
	"	2001	1994 - 1999	Venezuela	4.30	3.05	1.25
13	Bruce and Bhabra	2006	1992 - 2002	New Zealand	-	-	-
14	Rinne and Vähämaa	2011	1988 - 2008	Finland	15.50	11.00	4.50
15	Öhrberg et al.	2014	2002 - 2013	Sweden	21.38	17.26	4.12
16	Wang et al.	2011	1994 - 2009	China	-	-	-
17	Yan et al.	2015	2003 - 2012	Taiwan	19.43	9.25	10.18
18	Qiu et al.	2013	1981 - 2010	Japan	13.61	3.97	9.64
19	Terence and Kin	2010	1992 - 2010	Hong Kong	-1.28	8.61	-9.89
20	Tissayakorn et al.	2013	1995 - 2012	Thailand	23.68	3.32	20.36

Numerous studies have been conducted on this topic with mixed findings. In the UK, Brzeszczynski et al. (2008) found evidence that DoD was able to outperform the market where Filbeck and Visscher (1997) had previously concluded the opposite for an earlier time period. In Canada, they later documented that DoD was profitable enough to compensate for transaction costs and taxes, and also able to generate higher risk-adjusted returns[5] during the first ten years of the index's existence Filbeck and Visscher (2003).

As the strategy gained traction due to its attractive profitability, academic studies eventually raised criticism regarding some of the applied methodology. In the US there is evidence that the DoD strategy is able to generate positive alpha, and many have linked the strategy to the broader theory of an overreaction by market participants (McQueen and Thorley, 1999; Domian et al., 1998). As pointed out by Domian et al. (1998), investment books like the one by O'Higgins and Downes (1991) and Knowles and Petty (1992) have popularised the DoD strategy, and seemingly made it less successful. They argued that, especially after the 1987 market crash, the strategy resulted in selecting stocks that were already outperforming the S&P500

[5] Measured by the Sharpe ratio and Treynor index.

and therefore could not be argued to be 'dogs' anymore. On the other hand, Hirschey (2000), Conrad and Kaul (1993) and Ball et al. (1995) advocated that the conclusion is drawn on the basis of errors attributable to data errors, wrongly computed returns or data mining.

Da Silva (2001) concluded that DoD constructed portfolios in Argentina, Chile, Colombia, Mexico and Venezuela were able to slightly outperform the market in terms of absolute and risk-adjusted return, but underperformed in the Brazilian market. The results were, however, not statistically significant.

In New Zealand, Bruce and Bhabra (2006) found that DoD consistently underperforms the market portfolio, both on an absolute and risk-adjusted basis. To explain their findings, they proposed that the illiquid nature of stocks listed on the stock exchange and the inverse relationship between value and price momentum could explanatory factors.

Rinne and Vähämaa (2011) studied the performance on the Finnish market in period 1988 - 2008, where they concluded that DoD outperformed the market after adjustments for risk, but not necessarily after taxes and transaction costs. Öhrberg et al. (2014) also showed that the DoD outperformed the Swedish market without statistically significant results.

In the Chinese, Taiwanese, Japanese, Hong Kong and Thai markets results have shown that, on average, the DoD has been successful and able to generate alpha, with the exception being the Hong Kong market (Wang et al., 2011; Yan et al., 2015; Qiu et al., 2013; Tissayakorn et al., 2013; Terence and Kin, 2010).

3 Data and Portfolio Construction

3.1 Return data and constructing the portfolios

At the outset of the study, two simulated 'funds' with an initial value of £10,000 were constructed to employ two strategies: the DoD portfolio employs the DoD strategy whereas the FTSE 100 passively invests in the FTSE 100 benchmark. Stock closing prices, dividend information and total returns for all 210 companies that have constituted the FTSE 100 in the time period 2001 - 2016 are retrieved from Bloomberg. Data was pulled one year prior to the start of the investment strategy to compute the dividend yields required to construct the first portfolio in 2002. The data was downloaded in spreadsheet form and subsequently manipulated with Python on which most of the analysis was carried out.

The retrieved dividend information contained information about ordinary dividends, rights issues, special cash dividends, stock splits and return of capital, but only information about ordinary dividends was deemed relevant for calculating dividend yield. Dividend payments announced in other currencies were converted into pounds at the historical exchange rate the day of the payment.

Then, following the framework of analysis outlined by Filbeck and Visscher (1997, 2003) and McQueen et al. (1997), dividends are annualised by multiplying the last dividend payment of the year with the number of dividend payments per year outlined in the company's payment schedule[6]:

[6] Therefore, quarterly dividends are multiplied by 4 whereas semi-annual payments are multiplied with 2.

$$\mathrm{D_{a,t}} = \mathrm{D} \times \mathrm{m} \tag{1}$$

Where:
$\mathrm{D_{a,t}}$ = Annualised dividend
D = Last ordinary dividend in the period
m = Number of dividend payments indicated by payment schedule

Trailing dividend yields are then computed as:

$$\text{Trailing Dividend Yield} = \frac{\mathrm{D_{a,t-1}}}{\mathrm{P}} \tag{2}$$

Where:
$\mathrm{D_{a,t-1}}$ = Annualised dividend for the previous year
P = Last year's final stock price

After calculating and ranking the dividend yields, an equally weighted portfolio (10% weight in each stock) is formed at the beginning of year t and then held until the first trading day of year $t+1$. The constructed portfolios are presented in Table 2:

Table 2: Constructed DoD portfolios from 2002 - 2016

2002		**2003**		**2004**		**2005**	
Cable & Wireless Communications Ltd	17.61	Severn Trent PLC	10.05	Scottish & Newcastle Ltd	10.58	J Sainsbury PLC	8.40
Invensys Ltd	9.69	Rolls-Royce Holdings PLC	9.35	United Utilities Group PLC	10.01	Dixons Retail Group Ltd	7.45
Severn Trent PLC	9.51	United Utilities Group PLC	9.08	Severn Trent PLC	9.32	Severn Trent PLC	7.39
United Utilities Group PLC	9.03	Scottish & Newcastle Ltd	8.38	Dixons Retail Group Ltd	7.40	United Utilities Group PLC	7.33
Scottish Power Ltd	7.38	RSA Insurance Group PLC	8.20	SSE PLC	7.28	GlaxoSmithKline PLC	6.55
Scottish & Newcastle Ltd	7.11	Scottish Power Ltd	7.92	J Sainsbury PLC	7.26	SSE PLC	6.05
SSE PLC	6.89	Gates Worldwide Ltd	7.78	Hays PLC	6.74	Tate & Lyle PLC	5.58
EMI Group Ltd	6.58	J Sainsbury PLC	7.76	Rolls-Royce Holdings PLC	5.64	BT Group PLC	5.22
Land Securities Group PLC	6.09	Hays PLC	7.60	BOC Group Ltd/The	5.51	BOC Group Ltd/The	4.93
Rolls-Royce Holdings PLC	6.01	Land Securities Group PLC	7.26	Land Securities Group PLC	5.24	Bunzl PLC	4.93
		Turnover	**0.40**	**Turnover**	**0.30**	**Turnover**	**0.40**
2006		**2007**		**2008**		**2009**	
Cable & Wireless Communications Ltd	11.15	Cable & Wireless Communications Ltd	9.90	Cable & Wireless Communications Ltd	11.24	Lloyds Banking Group PLC	18.10
Dixons Retail Group Ltd	7.60	Vodafone Group PLC	7.88	BT Group PLC	7.33	Cable & Wireless Communications Ltd	16.10
United Utilities Group PLC	7.05	Dixons Retail Group Ltd	6.82	Vodafone Group PLC	6.89	BT Group PLC	15.38
Severn Trent PLC	6.83	Severn Trent PLC	6.52	United Utilities Group PLC	6.19	Barclays PLC	14.99
SSE PLC	5.98	United Utilities Group PLC	5.86	Alliance & Leicester Ltd	5.80	Marks & Spencer Group PLC	13.22
BT Group PLC	5.84	BT Group PLC	5.04	Home Retail Group PLC	5.49	Vodafone Group PLC	10.59
National Grid PLC	5.59	Alliance Boots Holdings Ltd	5.01	Taylor Wimpey PLC	5.41	United Utilities Group PLC	10.05
Tate & Lyle PLC	4.87	SSE PLC	4.21	Wolseley PLC	5.38	Man Group PLC	10.01
Alliance Boots Holdings Ltd	4.67	National Grid PLC	3.96	Kingfisher PLC	5.29	Home Retail Group PLC	9.46
LHR Airports Ltd	4.56	Diageo PLC	3.82	Severn Trent PLC	5.07	Intu Properties PLC	8.94
Turnover	**0.40**	**Turnover**	**0.20**	**Turnover**	**0.50**	**Turnover**	**0.50**
2010		**2011**		**2012**		**2013**	
Cable & Wireless Communications Ltd	20.08	Vodafone Group PLC	9.99	Vodafone Group PLC	9.86	Vodafone Group PLC	11.96
Vodafone Group PLC	10.46	National Grid PLC	8.24	Man Group PLC	9.47	SSE PLC	7.91
United Utilities Group PLC	8.88	SSE PLC	8.00	ICAP PLC	8.46	HSBC Holdings PLC	6.88
SSE PLC	7.94	United Utilities Group PLC	7.81	SSE PLC	8.15	J Sainsbury PLC	6.72
Man Group PLC	7.61	Severn Trent PLC	6.17	J Sainsbury PLC	7.13	National Grid PLC	6.61
Severn Trent PLC	7.60	J Sainsbury PLC	5.42	Marks & Spencer Group PLC	6.95	United Utilities Group PLC	6.34
Home Retail Group PLC	6.77	Marks & Spencer Group PLC	5.15	National Grid PLC	6.88	Friends Life Group Ltd	5.70
National Grid PLC	6.20	BT Group PLC	5.09	Aviva PLC	6.65	Marks & Spencer Group PLC	5.65
Rexam Ltd	6.08	RSA Insurance Group PLC	4.98	United Utilities Group PLC	6.60	RSA Insurance Group PLC	5.43
J Sainsbury PLC	5.92	Royal Dutch Shell PLC	4.98	RSA Insurance Group PLC	6.35	Aviva PLC	5.36
Turnover	**0.50**	**Turnover**	**0.40**	**Turnover**	**0.30**	**Turnover**	**0.20**
2014		**2015**		**2016**			
Vodafone Group PLC	8.70	J Sainsbury PLC	9.97	Anglo American PLC	13.71		
SSE PLC	8.61	HSBC Holdings PLC	8.26	BHP Billiton PLC	10.77	**Average turnover**	**0.35**
HSBC Holdings PLC	7.47	SSE PLC	7.48	HSBC Holdings PLC	9.84		
United Utilities Group PLC	6.81	Vodafone Group PLC	6.61	Royal Dutch Shell PLC	8.22		
J Sainsbury PLC	6.52	BP PLC	6.21	SSE PLC	8.09		
National Grid PLC	6.13	Royal Mail PLC	6.19	BP PLC	7.50		
Severn Trent PLC	5.34	BHP Billiton PLC	5.84	Rio Tinto PLC	6.96		
Royal Dutch Shell PLC	5.09	Royal Dutch Shell PLC	5.58	Vodafone Group PLC	6.64		
Marks & Spencer Group PLC	4.99	GlaxoSmithKline PLC	5.52	Royal Mail PLC	6.44		
RSA Insurance Group PLC	4.99	National Grid PLC	5.50	J Sainsbury PLC	6.34		
Turnover	**0.20**	**Turnover**	**0.40**	**Turnover**	**0.20**		

Note: Constructed DoD portfolios from 2002 - 2016 according to their dividend yield on the first trading day each year (dividend yield in corresponding column). The turnover rate expresses how many companies are replaced in the DoD portfolio every year

As seen from Table 2, a total of 46 companies constituting the DoD portfolio from 2002 to 2016. Of those, 18 companies appeared only once, whereas 5 companies appeared 10 or more times during the period of review. The average turnover in the DoD portfolio is 0.35, and ranges from 2 to 5 companies.[7] Following the framework of McQueen et al. (1997), I use a one-way transaction cost of 1%, and employ equation 3 to compute an average transaction cost for the DoD portfolios of 0.70%:[8] As the DoD strategy requires annual rebalancing, it fails to consider the potential asymmetry of costs between past winners and losers among other elements of market micro structure – potentially leading to an over-/underestimation of the results.[9]

$$\text{Transaction cost} = 2 \times \text{Average Turnover} \times 1\% \tag{3}$$

The strategy consists of an equally weighted portfolio consisting of ten stocks. In line with good practice for academic studies, equation 4 is employed to compute returns for the constructed portfolio.

$$\mathrm{r_{P,t}} = \ln\left[\frac{1}{\mathrm{N}}\left(\frac{\mathrm{S_{1,t}}}{\mathrm{S_{1,t-1}}} + \frac{\mathrm{S_{2,t}}}{\mathrm{S_{2,t-1}}} + \cdots + \frac{\mathrm{S_{N,t}}}{\mathrm{S_{N,t-1}}}\right)\right] \tag{4}$$

Where:
$\mathrm{r_{S,t}}$ = Log return of portfolio P at time t
$\mathrm{S_{i,t}}$ = Asset i's price at time t
$\mathrm{S_{i,t-1}}$ = Asset i's price at time *t - 1*
N = Number of assets included in portfolio

The logarithmic return is widely employed in financial literature due to its favourable properties for use in statistical analysis compared to simple net returns (Brooks, 2014).[10]

3.2 Outliers and acquisitons

In the event where a company included in the DoD portfolio was acquired or merged during the period of review, the proceeds would be invested in the market portfolio for the remainder of the year. If a company entered administration, a 100% loss would be taken. The following notable company events affecting the DoD portfolio occurred during the period:

[7] Full overview is presented in appendix A.
[8] $2 \times 0.35 \times 0.01 = 0.007$.
[9] For example, Li et al. (2009) review the relationship between trading volumes, transactions costs, and the profitability of momentum strategies in the UK where they found that transactions costs for selling loser firms are around twice those of buying winners.
[10] Simple net returns would be $= \frac{\mathrm{S_t}}{\mathrm{S_{t-1}}} - 1$.

– 2006: LHR Airports Ltd (formerly known as BAA PLC) was acquired by Ferrovial.[11]

– In 2007, AB Acquisitions Holdings Limited in conjunction with Stefano Pessina and KKR acquired Alliance Boots Holdings Ltd.[12]

– In 2008, Alliance & Leicester was acquired by the Spanish Santander Group.[13]

3.3 Fama & French and Carhart

The study also employs data for the national benchmark factors proposed by the Fama and French (1993) model (equation 6) and the Carhart (1997) model (equation 7), which was retrieved for the UK market from Gregory et al. (2013).[14] The factors extend the traditional CAPM model (equation 5) by including factors that capture size effect (SMB), book-to-market (HML) and momentum effects (UMD).

CAPM:
$$R_{i,t} - R_{f,t} = \alpha_p + \beta_i(R_{mt} - R_{ft}) + \varepsilon_t \tag{5}$$

Fama, French:
$$R_{i,t} - R_{f,t} = \alpha_p + \beta_i(R_{mt} - R_{ft}) + \gamma_i SMB_t + \delta_i HML_t + \varepsilon_t \tag{6}$$

Carhart:
$$R_{i,t} - R_{f,t} = \alpha_p + \beta_i(R_{mt} - R_{ft}) + \gamma_i SMB_t + \delta_i HML_t + \lambda_i UMD_t + \varepsilon_t \tag{7}$$

α_p is Jensen's (1968) alpha, which measures the portfolio's systematic return compared to the market return for comparable level of risk, and ε_t represents the random residual term for each observation (Lintner, 1965; Mossin, 1966; Sharpe, 1964).

$R_{mt} - R_{ft}$ measures the excess return on the market over a risk-free rate. The size effect can be defined as the return of a portfolio with long positions in small stocks and short positions in large stocks. Book-to-market represents the return of a portfolio with long positions in high book-to-market stocks and short-selling low book-to-market stocks. The momentum factor represents the return of a portfolio that is long in 'winner' stocks and short in 'loser' stocks. γ_i, δ_i and λ_i measure the exposure to the respective investment style.

The 3-month Treasury bill is employed as the risk-free rate in this study.[15] After transforming the stated rate into a monthly rate by employing equation 8, the lagged value of the rate is used to compute monthly differences.

$$R_{f,t,1m} = \ln\left((1 + SR_{f,t,13w}\frac{91}{365.25})^{\frac{30.4375}{91}}\right) \tag{8}$$

Where:
$SR_{f,t,13w}$ = Stated 13 weeks risk-free rate at time t

[11] Ferrovial, *History of Ferrovial Airports*, n.d.. Available at: http://www.ferrovial.com/en/business-lines/airports/about-airports/history-of-ferrovial-airports/

[12] Financial Times - Rigby, Elizabeth, April 24, 2007, *KKR wins £11.1bn battle for Boots*. Available at: https://www.ft.com/content/039d3500-f1fb-11db-b5b6-000b5df10621

[13] Financial Times - Vincent, Matthew, May 27, 2009, *Abbey, Alliance & Leicester and B&B to disappear from the high street*. Available at: https://www.ft.com/content/fdea9550-4ade-11de-87c2-00144feabdc0

[14] Available online at: http://business-school.exeter.ac.uk/research/centres/xfi/famafrench/files/.

[15] Data was pulled from Bank of England's web pages

4 Results and Analysis

This section presents the performance of the 'Dogs of the Dow' portfolio relative to the FTSE 100 benchmark, and the measures used to assess the performance. Absolute risk measures will be presented first before proceeding to relative risk measures and the CAPM, Fama & French and Carhart regression models.

4.1 Absolute Risk Measures

From Figure 1, we see that the DoD strategy's terminal value (43,100) is 3.14x higher than the FTSE 100 benchmark (13,690) and thus seems to be superior to the benchmark in terms of absolute values.

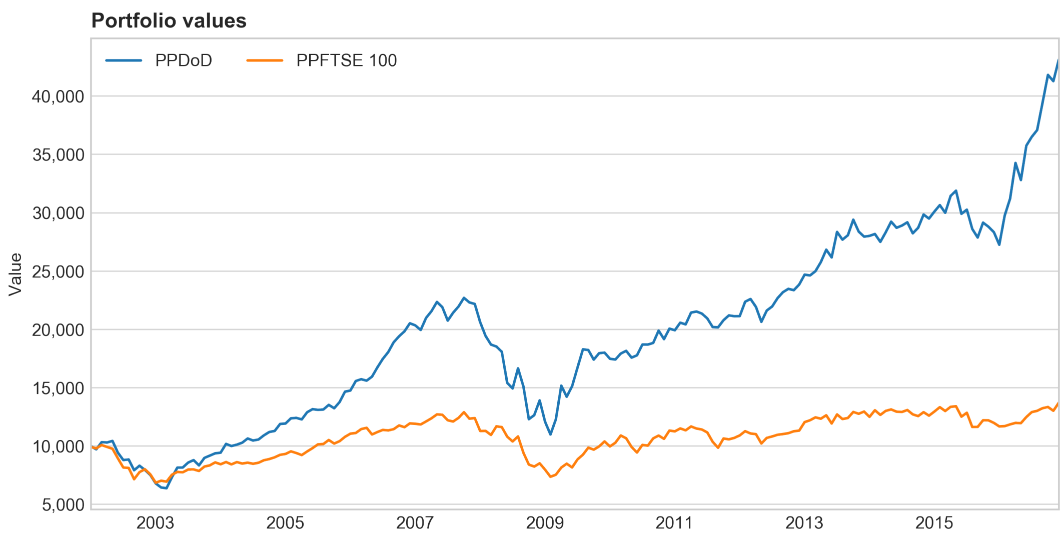


Figure 1: Portfolio values

Table 3: Overview over portfolio performances in the period 2002 - 2016

	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
DoD (%)	-28.84	22.18	23.82	20.97	33.68	7.77	-46.70	25.84	10.83	5.16	12.12	15.88	5.39	-4.03	42.01
FTSE 100 (%)	-28.07	12.76	7.27	15.45	10.18	3.73	-37.58	19.94	8.62	-5.71	5.68	13.48	-2.75	-5.06	13.48
DoD - FTSE 100 (%)	-0.76	9.41	16.55	5.52	23.51	4.05	-9.12	5.90	2.21	10.88	6.45	2.40	8.14	1.03	28.53

Results of empirical tests conducted by Price et al. (1982) provide evidence that standard deviation as a metric exhibits systematic tendencies when estimating risk for securities with different exposure to systematic risk. Because of its rather simplistic, but intuitive, approach, the standard deviation derived from an estimate of variance is commonly used by practitioners when quantifying asset risk. However, as standard deviation incorporates the sum of squared vertical distances of returns from the mean, it is effectively eliminating the notion of positive or negative asset movements. Hence, large positive deviations are treated the same way as negative deviations - and will therefore 'increase' the asset perceived risk rather than treating them as a beneficial movement.

[Figlewski (1997)] also pointed out that when calculating the standard deviation, it's implicitly assumed to be constant over the period of review, whereas Figure 2 and 3 clearly demonstrate that's not the case for our portfolio.

The general formulas for excess return variance and standard deviation are given by equation 9 and 10. Standard deviation computed on the basis of monthly log returns can then be annualised with the square root of time, as illustrated in equation 11 (Rakkestad, 2002).

$$\sigma_{xp}^2 = \frac{1}{T-1}\sum_{t=1}^{T}\left(r_{xp,t} - \bar{r}_{xp}\right) \tag{9}$$

$$\sigma_{xp} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(r_{xp,t} - \bar{r}_{xp}\right)} \tag{10}$$

$$\sigma_{xp,a} = \sigma_{xp,h} \times \sqrt{h} \tag{11}$$

Where:
$r_{xp,t}$ = Portfolio's excess return over risk-free rate at time t
$\bar{r}_{xp}$ = Mean of portfolio's excess return over risk-free rate
T = Number of observations
h = Number of h periods in a year

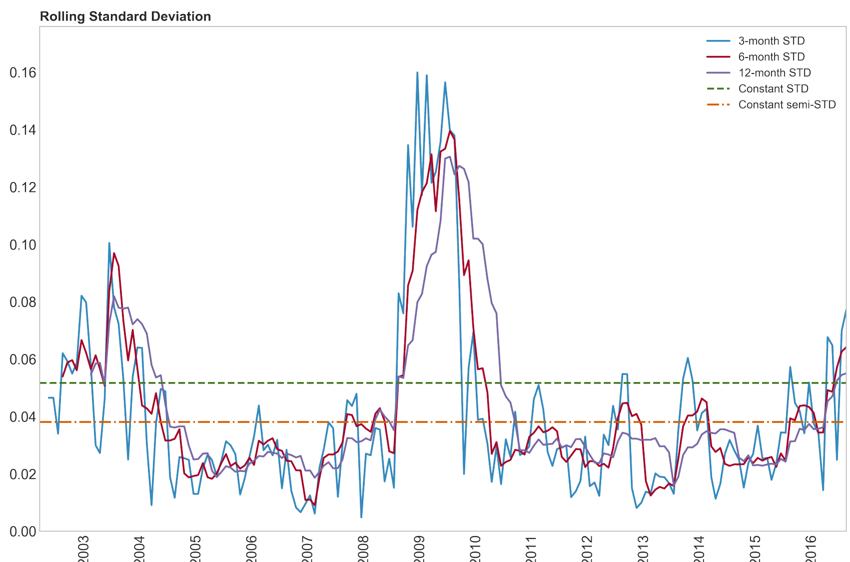


Figure 2: Rolling standard deviation for the DoD portfolio with rolling windows of 3, 6 and 9 months (not annualised)

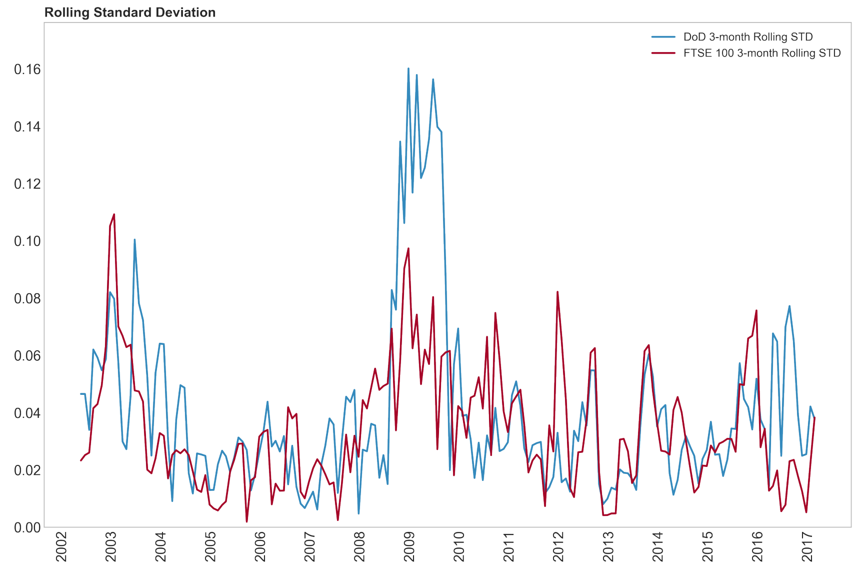


Figure 3: 3 month rolling standard deviation for the DoD portfolio and the FTSE 100 (not annualised)

Partly in response to the critique, Lower Partial Moment (LPM) was introduced as a mitigating alternative (Eling and Schuhmacher, 2007; Sortino and Van Der Meer, 1991). It measures only risk that originates from negative deviations of the observed returns below an investor's minimal acceptable return, Ψ. The minimal acceptable return for an investor could be the expected return, the risk-free rate or simply zero. Equation 12 gives the general formula for computing LPM for security i[16], and Table 4 presents descriptive statistics. Although the DoD portfolio had higher mean return, it seems to be affiliated by taking higher risk as suggested by McQueen et al. (1997).

$$\mathrm{LPM}_{q,p}(\Psi) = \frac{1}{N-1}\sum_{t=1}^{T} \max\left[\Psi - r_{i,t}, 0\right]^{q} \tag{12}$$

Where:

Ψ = Investor's minimal acceptable return

$r_{i,t}$ = Excess return on asset i at time t

q = a weighting factor for the deviation from Ψ

Semi-variance: $$\mathrm{SV}_{xp} = \mathrm{LPM}_{2,p}(\bar{r}_{xp}) \tag{13}$$

Semi-standard deviation: $$\mathrm{SSD}_{xp} = \sqrt{\mathrm{LPM}_{2,p}(\bar{r}_{xp})} \tag{14}$$

[16] Semi-variance (and subsequently, semi-standard deviation) are a special case of the LPM where q = 2 and $\Psi = \bar{r}_{xp}$ (Jaaman et al., 2011).

Table 4: Descriptive Statistics

	DoD - R_f	FTSE 100 - R_f
Mean	6.43%	-0.84%
Median	9.37%	6.25%
Variance	3.21%	2.021%
Semi-variance	1.746%	1.227%
Std. Dev.	17.91%	14.22%
Semi-Std. Dev.	13.21%	11.08%
Correlation	0.7407	
Covariance	1.885%	

*All figures are annualised

4.1.1 Jarque-Bera

A test for normality is conducted before proceeding with further analysis, as it is the most commonly made assumption in statistical research. In a classic OLS regression model, it is assumed that the disturbance term, ε_t, is normally distributed (Brooks, 2014; Thadewald and Bning, 2007). Deviation from normality may cause inaccurate estimations or misinterpretation of data. One of the most applied tests for normality is the Jarque-Bera goodness-of-fit test (Jarque and Bera, 1980), where the test statistics is computed based on the sample data's skewness and kurtosis, and subsequently compared to a normal distribution.[17] Two hypotheses are formulated to conduct the test:

$$H_0 : \text{Normal distribution, zero skewness and excess kurtosis}$$
$$H_1 : \text{Non-normal distribution}$$

To compute JB test statistics, equation 15 is employed, which are then compared to a χ^2-distribution with two degrees of freedom. For $\alpha = 5\%$, the appropriate critical value is 5.99.

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{15}$$

Where:
n = Number of observations in sample data
S = Sample data's estimated skewness
K = Sample data's estimated kurtosis

Presumably, just by studying Figure 4a and 4b, one can presume that DoD's excess returns are normally

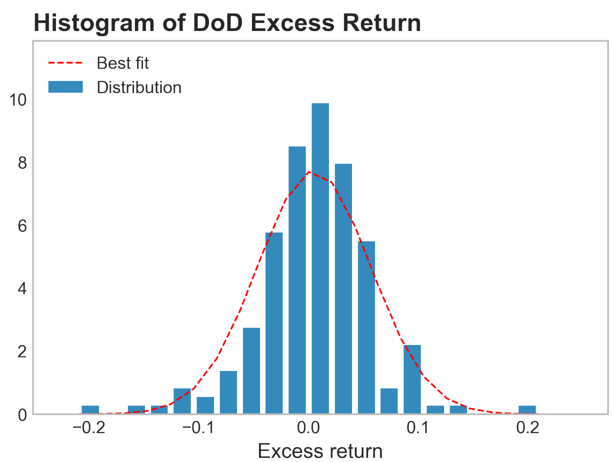
[17] For a normal distribution, we assume a skewness S and kurtosis K of 0 and 3, respectively.

distributed whereas FTSE 100's are not. The computed test statistics are 3.86 and 43.13 for DoD and FTSE 100, respectively. This confirms that DoD excess returns are normally distributed whereas FTSE 100's are not. The implication would be that standard deviation would be considered inadequate as a risk measure for e.g. asset allocation, and hence other measures would be more accurate.

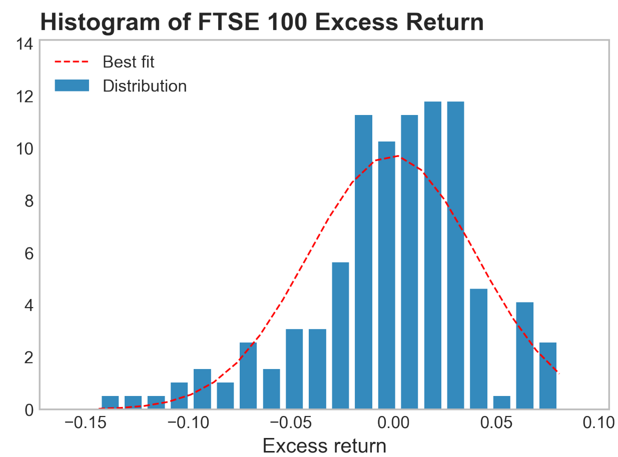
Table 5: Skewness, kurtosis and Jarque-Bera

	DoD	FTSE 100
Skewness	-0.36	-0.80
Excess Kurtosis	0.11	-1.84
Jarque-Bera	3.86	43.1304**

** 5% significance level



(a) DoD excess return histogram



(b) FTSE 100 excess return histogram

4.1.2 Maximum Drawdown

Maximum drawdown is a helpful metric that provides an indication of the portfolio's downside risk, and it is calculated as the highest relative reduction in the portfolios value over a given time (Magdon-Ismail et al., 2004). Formal definition is given in equation 16:

$$\mathrm{DD_{qs,T,p}} = \left|\min\left[\frac{\mathrm{P_{tp}} - \mathrm{P_{t-n,p}}}{\mathrm{P_{t-n,p}}}\right]\right|^{\mathrm{q}}, \text{ with t=(1,2,..,T), n = (1,2,..,T) and n} < \mathrm{T} \tag{16}$$

$$\text{if } \frac{1}{\mathrm{n}}\sum_{\mathrm{m=1}}^{\mathrm{m=n}} \frac{\mathrm{P_{t-m+1,p}} - \mathrm{P_{t-m,p}}}{|\mathrm{P_{t-m+1,p}} - \mathrm{P_{t-m,p}}|} = -1, \text{ otherwise } \mathrm{DD_{qsTp}} = 0$$

Table 6: Maximum Drawdown metrics

	DoD	FTSE 100
Maximum Drawdown	-51.66%	-43.02%

In other words, the maximum drawdown indicates the maximum loss the fund occurred over a certain period of time, and is helpful when assessing the portfolio's performance during market downturns. From Figure 5 and Table 6, we notice that the portfolio suffers severe losses, and even performs worse than the benchmark, during the financial crisis. A portfolio's ability to preserve capital and yield a steady performance are essential when investing with such a passive, long-term strategy. If we exclude the extreme impact of the crisis in 08-09' and focuses on the performance from 2009 onwards, we notice a much lower maximum drawdown where the DoD portfolio performs better (-14.55%) than the benchmark (-15.69%).

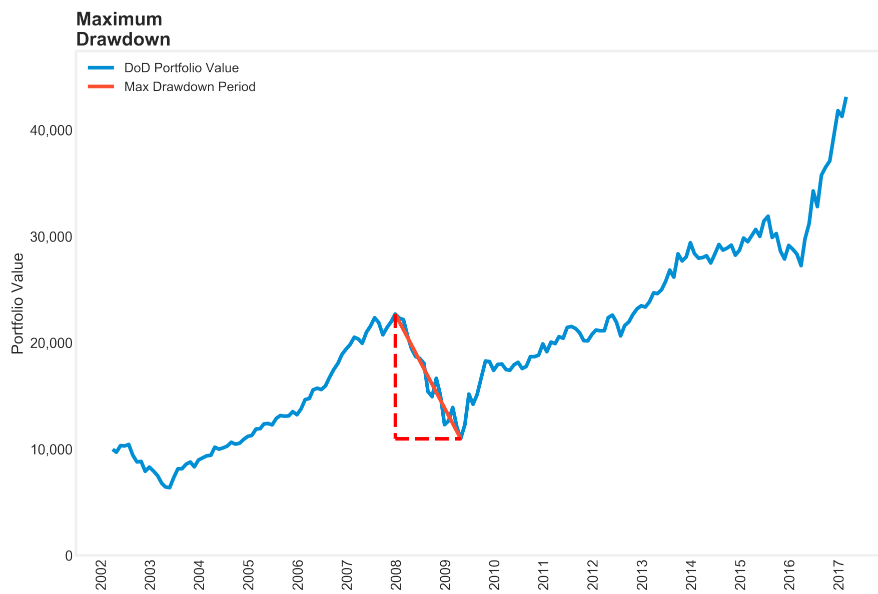


Figure 5: Illustration of maximum drawdown

4.1.3 Value-at-Risk and Expected Shortfall

Value-at-Risk (VaR) is an estimate of the maximum loss that you are $1 - \alpha$ certain to have, but it does not provide insight for the potential losses, nor its distribution, when the VaR is exceeded (Alexander, 2009). Historical VaR is derived as the lower α percentile after ranking the vector of fund returns in ascending order.

Expected shortfall (ES) can be defined as the average of the losses occurred when VaR is exceeded.[18] According to Bhattacharyya et al. (2008), the VaR estimate based on an assumption of normality may underestimate the actual risk if asymmetry, excess kurtosis and volatility are not properly incorporated into

[18] Sometimes referred to as conditional VaR (cVaR) or expected tail loss (ETL).

the model. For the conditional VaR, however, the distribution of losses exceeding VaR is to a larger extent taken into account, and therefore provides a better measure of the underlying risk.

The figures for VaR and ES provide evidence that VaR underestimates the risk, as the VaR for the DoD portfolio is larger than for the FTSE 100 (-7.34% vs. -8.01%) whereas the average absolute value of losses exceeding VaR is larger for DoD than for FTSE 100 (-12.67% vs. -10.67%).[19] This can also be noted from Figure 4a and 4b, where the DoD portfolio has a larger negative tail.

Table 7: Value-at-Risk and Expected Shortfall

	DoD	**FTSE 100**
VaR	-7.34%	-8.01%
ES	-12.67%	-10.67%

4.2 Relative Risk Measures

4.2.1 Sharpe Ratio

The Sharpe ratio (Lintner, 1965) measures the risk-adjusted performance of an asset over a risk-free alternative, where the total risk of the portfolio is expressed through its standard deviation.

$$\mathrm{SR_p} = \frac{\bar{\mathrm{r}}_{\mathrm{xp}}}{\sigma_{\mathrm{xp}}} \tag{17}$$

Where:
$\bar{\mathrm{r}}_{\mathrm{xp}}$ = Mean excess return
σ_{xp} = Standard deviation of excess return

Despite its popularity and applicability since its origination, the SR has been proven to exhibit some unfortunate attributes.[20] For instance, when excess return is negative, the reliability of the SR measure significantly decreases (Israelsen, 2005, 2010). In addition, the problems discussed in section 4.1 are also present, which has led to the rise of risk measures based on semi-standard deviation such as the Sortino ratio (Sortino and Price, 1994).

Of the two portfolios, only the DoD portfolio is able to yield positive excess return per unit of extra volatility with a SR of 0.10362 whereas the FTSE 100 exhibits a negative SR of -0.01697 - indicating a decline in return if additional risk is taken.

Table 8: Sharpe ratios

	DoD	**FTSE 100**
Sharpe	0.10362	-0.01697

[19] All figures are monthly.
[20] See Sharpe (1994) for a published restatement of the Sharpe ratio.

4.2.2 Modigliani's Risk-Adjusted Performance Alternative Ratio (RAPA)

Other point to the lack of intuitive dimension as yet another drawback of the metric, making comparisons between several investments difficult or misleading. Modigliani's Risk-Adjusted Performance Alternative Ratio[21] (Modigliani and Modigliani, 1997) is derived from the Sharpe ratio, but it is more intuitive to interpret as it scales the ratio using the volatility of the benchmark - giving it its favourable attribute that it yields excess returns adjusted to its benchmark portfolio.

$$\mathrm{RAPA} = \bar{\mathrm{r}}_{\mathrm{xp}} \frac{\sigma_{\mathrm{xm}}}{\sigma_{\mathrm{xp}}} \tag{18}$$

Where:
$\bar{\mathrm{r}}_{\mathrm{xp}}$ = Mean excess return
σ_{xp} = Standard deviation of excess return for portfolio
σ_{xm} = Standard deviation of excess return for market

We notice that the DoD portfolio still outperforms its benchmark, and it still manages to generate positive excess return by taking on additional risk.

Table 9: Sharpe and RAPA ratios

	DoD	**FTSE 100**
Sharpe	0.10362	-0.01697
RAPA	0.004252	-0.0007

4.2.3 Treynor Ratio

Treynor ratio (Treynor, 2009) is another metric to assess the excess returns over a risk-free rate per unit of market risk expressed through the portfolio's beta. As the metric utilises the portfolio beta in its denominator, it focuses on the risk that cannot be diversified away. If the Treynor ratio is high, the manager is able to generate high returns per unit of market risk taken.

$$\mathrm{T}_{\mathrm{xp}} = \frac{\bar{\mathrm{r}}_{\mathrm{xp}}}{\beta_{\mathrm{p}}} \tag{19}$$

Where:
$\bar{\mathrm{r}}_{\mathrm{xp}}$ = Mean excess return
β_{p} = Portfolio's sensitivity to the market, estimated by a Carhart four factor model

[21] Also known as M^2, M2, Modigliani-Modigliani measure or RAPA.

Here, with a positive coefficient of 0.0057, the DoD is able to generate a slightly positive excess return per unit of market risk, which is in contrast to the negative excess return on the FTSE 100.

In relation to the Sharpe ratio, one can notice that the majority of the excess return is generated on the basis of taking extra idiosyncratic risk.

Table 10: Sharpe and Treynor ratios

	DoD	**FTSE 100**
Sharpe	0.10362	-0.01697
Treynor	0.006387	-0.0007

4.2.4 Sortino Ratio

As previously mentioned in Section 4.2.1, Sortino and Price (1994) developed the Sortino ratio as a variant of Sharpe ratio, where the commonly used standard deviation metric in the denominator is replaced with semi-standard deviation that only quantifies downside deviations.

$$\mathrm{SO_{xp}} = \frac{\bar{\mathrm{r}}_{\mathrm{xp}}}{\sqrt{\mathrm{LPM}(\Psi)_{\mathrm{q,p}}}} \tag{20}$$

Where:
$\bar{\mathrm{r}}_{\mathrm{xp}}$ = Portfolio's excess return over risk-free rate
Ψ = The LPM threshold, which is set to $\bar{\mathrm{r}}_{\mathrm{xp}}$
$\mathrm{q} = 2$

Having established that the distribution of FTSE 100 is non-normal and negatively skewed, we get a more nuanced, and possibly more accurate, picture of the relationship between investors' risk-return preferences and the performance of the two portfolios by utilising the Sortino ratio. As presented in Table 11, the DoD still outperforms the benchmark when it comes to generate excess return per unit of downside risk with a coefficient of 0.140426. As for the benchmark (-0.02177), its fat left tail seems to be 'penalised' by the Sortino ratio, and the performance based on the measure is exacerbated.

Table 11: Sharpe and Sortino ratios

	DoD	**FTSE 100**
Sharpe	0.10362	-0.01697
Sortino	0.140426	-0.02177

4.2.5 Return on Probability of Shortfall (RoPS)

$$\mathrm{RoPS_{xp}} = \frac{\bar{\mathrm{r}}_{\mathrm{xp}}}{\mathrm{LPM}(\Psi)_{\mathrm{q,p}}} \tag{21}$$

Where:
q = 0

Probability of shortfall is a measure derived from LPM in which the probability that a portfolio is unable to generate a minimum acceptable return is quantified. This measure is useful for an investor to help raise awareness of the investor's attitude to risk. From Table 12, one can see that the DoD portfolio is able to generate a small compensation for the risk of a significant decrease in portfolio value.

Table 12: Return on Probability of Shortfall

	DoD	**FTSE 100**
Probability of Shortfall	47.98%	46.24%
Return on Prob. of Shortfall	0.0112	-0.0015

4.3 CAPM, Fama & French and Carhart factor models

Table 13 presents the results. We notice that a slightly positive and significant alpha increases as we control for additional investment styles in the model. By taking into account the transaction cost computed in section 3.1 (= 0.70%), it is evident that the portfolio is able to generate positive risk-adjusted and transaction cost-adjusted return. A positive β-loading of .86 signals that the portfolio quite closely follows the market, and a significantly positive γ-loading indicates that it does so by having larger exposure to smaller cap companies than large cap. The significantly negative λ-loading suggests that the portfolio is more sensitive to 'loser' stocks, and thus provides supporting evidence for the 'winner-loser' effect promoted by Domian et al. (1998). Also worth noticing is that the model is able to explain a larger proportion of the variation in the returns as more factors are included in the model.

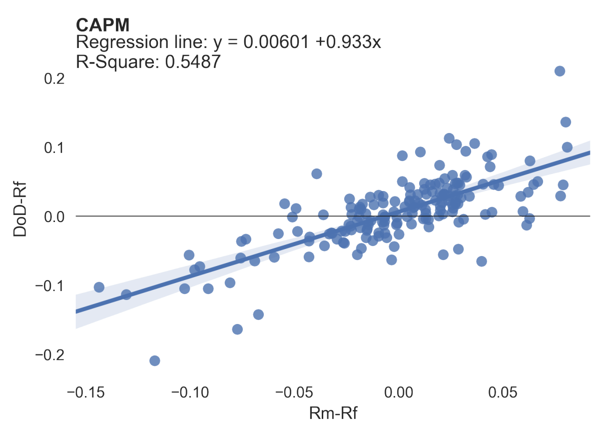


Figure 6: Scatter diagram of the 'DoD' portfolio

Table 13: Performance results for CAPM, Fama & French and Carhart

	Coefficients						Adj.
Model	α	β	γ	δ	λ	**R-square**	**R-square**
CAPM	0.00601**	0.93301***				0.5487	0.5461
Fama, French	0.00568**	0.86246***	0.21789***	0.30032***		0.5917	0.5845
Carhart	0.00807***	0.83851***	0.1335*	0.1278	-0.24438***	0.6277	0.6189

* 10% significance level, ** 5% significance level, *** 1% significance level

Table 14: Overview of risk measures

Absolute risk measures	**DoD**	**FTSE 100**
Lower Partial Moment (LPM)[a]	0.00145	0.00102
Variance(b)	3.21%	2.021%
Semi-Variance(b)	1.746%	1.227%
Standard Deviation[b]	17.91%	14.22%
Semi-Standard Deviation[b]	13.21%	11.08%
Correlation	0.7407	
Covariance[b]	1.885%	
Excess Kurtosis	0.110	-1.838
Skewness	-0.361	-0.802
Jarque-Bera[c]	3.8571	43.1304**
Maximum Drawdown	-51.66%	-43.02%
Value-at-Risk	-7.338%	-8.01%
Expected Shortfall	-12.67%	-10.67%

Relative Risk Measures	**DoD**	**FTSE 100**
Sharpe	0.1036	-0.0170
M2	0.0043	-0.001
Treynor	0.006387	-0.001
Sortino	0.1404	-0.022
Probability of Shortfall	47.98%	46.24%
Return on Prob. of Shortfall	0.0112	-0.0015
Sterling	0.1203	-0.0188
Burke	0.0864	-0.0123

a: LPM is computed using $\Psi = 0$ and q = 2
b: Figures are annualised
c: ** indicates a 5% significance level

5 Conclusion

This study re-examines the performance of the controversial 'Dogs of the Dow' strategy during the period 2002 - 2016. Unlike McQueen et al. (1997), I find that after controlling for investment style factors proposed by Fama and French (1993) and Carhart (1997), the Dow strategy has shown to outperform the FTSE market index in risk-adjusted terms for the sample period. By controlling for the momentum factor, there is evidence that the outperformance could be attributed to the 'winner - loser' effect, which is in line with the findings of Domian et al. (1998) and Rinne and Vähämaa (2011).

The average (median) excess return of 6.43% (9.37%) also compensates transaction cost, hence the Dow strategy also outperforms in terms of nominal measures. In terms of risk measures, the DoD portfolio beat the benchmark on all parameters.

However, to say anything about the true economic significance is beyond the scope of this paper, as the impact of taxation is also not properly taken into account as a simplifying assumption. In addition, results have not been tested for any 'seasonality' anomalies. As individuals in the UK start their tax year April 6th, the results could prove to be sensitive to using alternative starting months for the trading strategy. The findings do raise a further question, such as how much of the body of work confirming the DoD's empirical success is as a result of data mining? If not, the absence of investor learning may indicate a challenge to efficient markets.

Areas for further study could be to implement mitigating actions to the limitations mentioned above, in addition to increase the sample period to cover all three previous studies' time periods to increase the robustness of the findings and reduce the probability of 'data mining'.

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Appendices

A - Company Appearances Map

Table 15: Overview over company appearances in the DoD portfolio 2002 - 2016

Company	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Sum
Alliance & Leicester Ltd							1									**1**
Alliance Boots Holdings Ltd					1	1										**2**
Anglo American PLC															1	**1**
Aviva PLC											1	1				**2**
BHP Billiton PLC														1	1	**2**
BOC Group Ltd/The			1	1												**2**
BP PLC														1	1	**2**
BT Group PLC				1	1	1	1	1		1						**6**
Barclays PLC								1								**1**
Bunzl PLC				1												**1**
Cable & Wireless Communications Ltd	1				1	1	1	1	1							**6**
Diageo PLC						1										**1**
Dixons Retail Group Ltd			1	1	1	1										**4**
EMI Group Ltd	1															**1**
Friends Life Group Ltd												1				**1**
Gates Worldwide Ltd		1														**1**
GlaxoSmithKline PLC				1										1		**2**
HSBC Holdings PLC												1	1	1	1	**4**
Hays PLC		1	1													**2**
Home Retail Group PLC							1	1	1							**3**
ICAP PLC											1					**1**
Intu Properties PLC								1								**1**
Invensys Ltd	1															**1**
J Sainsbury PLC		1	1	1					1	1	1	1	1	1	1	**10**
Kingfisher PLC							1									**1**
LHR Airports Ltd					1											**1**
Land Securities Group PLC	1	1	1													**3**
Lloyds Banking Group PLC								1								**1**
Man Group PLC								1	1		1					**3**
Marks & Spencer Group PLC								1		1	1	1	1			**5**
National Grid PLC					1	1			1	1	1	1	1	1		**8**
RSA Insurance Group PLC		1								1	1	1	1			**5**
Rexam Ltd									1							**1**
Rio Tinto PLC															1	**1**
Rolls-Royce Holdings PLC	1	1	1													**3**
Royal Dutch Shell PLC										1			1	1	1	**4**
Royal Mail PLC														1	1	**2**
SSE PLC	1		1	1	1	1			1	1	1	1	1	1	1	**12**
Scottish & Newcastle Ltd	1	1	1													**3**
Scottish Power Ltd	1	1														**2**
Severn Trent PLC	1	1	1	1	1	1	1		1	1			1			**10**
Tate & Lyle PLC				1	1											**2**
Taylor Wimpey PLC							1									**1**
United Utilities Group PLC	1	1	1	1	1	1	1	1	1	1	1	1	1			**13**
Vodafone Group PLC						1	1	1	1	1	1	1	1	1	1	**10**
Wolseley PLC							1									**1**
Sum	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	

B - FTSE 100 Historical Constituents

Table 16: Overview over FTSE 100 historical constituents

01/01/2002	01/01/2003	01/01/2004	01/01/2005	01/01/2006
3i Group PLC	3i Group PLC	3i Group PLC	3i Group PLC	3i Group PLC
Alliance & Leicester Ltd	Alliance & Leicester Ltd	Alliance & Leicester Ltd	Alliance & Leicester Ltd	Alliance & Leicester Ltd
Alliance Boots Holdings Ltd	Alliance Boots Holdings Ltd	Alliance Boots Holdings Ltd	Alliance Boots Holdings Ltd	Alliance Boots Holdings Ltd
Allied Domecq Ltd	Alliance UniChem PLC	Alliance UniChem PLC	Alliance UniChem PLC	Alliance UniChem PLC
Anglo American PLC	Allied Domecq Ltd	Allied Domecq Ltd	Allied Domecq Ltd	Anglo American PLC
ARM Holdings PLC	Anglo American PLC	Anglo American PLC	Anglo American PLC	Antofagasta PLC
Associated British Foods PLC	Ascential Group Ltd	Ascential Group Ltd	Antofagasta PLC	Associated British Foods PLC
AstraZeneca PLC	Associated British Foods PLC	Associated British Foods PLC	Ascential Group Ltd	AstraZeneca PLC
Aviva PLC	AstraZeneca PLC	AstraZeneca PLC	Associated British Foods PLC	Aviva PLC
BAE Systems PLC	Aviva PLC	Aviva PLC	AstraZeneca PLC	BAE Systems PLC
Barclays PLC	BAE Systems PLC	BAE Systems PLC	Aviva PLC	Barclays PLC
BG Group Ltd	Barclays PLC	Barclays PLC	BAE Systems PLC	BG Group Ltd
BHP Billiton PLC	BG Group Ltd	BG Group Ltd	Barclays PLC	BHP Billiton PLC
BIP Industries Ltd	BHP Billiton PLC	BHP Billiton PLC	BG Group Ltd	BIP Industries Ltd
BOC Group Ltd/The	BOC Group Ltd/The	BOC Group Ltd/The	BHP Billiton PLC	BOC Group Ltd/The
BP PLC	BP PLC	BP PLC	BOC Group Ltd/The	BP PLC
British American Tobacco PLC	Bradford & Bingley PLC	Bradford & Bingley PLC	BP PLC	British American Tobacco PLC
British Land Co PLC/The	British American Tobacco PLC	British American Tobacco PLC	British American Tobacco PLC	British Land Co PLC/The
BT Group PLC	British Land Co PLC/The	British Land Co PLC/The	British Land Co PLC/The	BT Group PLC
Cable & Wireless Communications Ltd	BT Group PLC	BT Group PLC	BT Group PLC	Bwin Party Digital Entertainment PLC
Cadbury Ltd	Bunzl PLC	Bunzl PLC	Bunzl PLC	Cable & Wireless Communications Ltd
Canary Wharf Group PLC	Cadbury Ltd	Cable & Wireless Communications Ltd	Cable & Wireless Communications Ltd	Cadbury Ltd
Capita PLC	Canary Wharf Group PLC	Cadbury Ltd	Cadbury Ltd	Cairn Energy PLC
Carnival PLC	Capita PLC	Carnival PLC	Cairn Energy PLC	Capita PLC
Celltech Group Ltd	Carnival PLC	Centrica PLC	Capita PLC	Carnival PLC
Centrica PLC	Centrica PLC	Compass Group PLC	Carnival PLC	Centrica PLC
Compass Group PLC	Compass Group PLC	Daily Mail & General Trust PLC	Centrica PLC	Compass Group PLC
Daily Mail & General Trust PLC	Daily Mail & General Trust PLC	Diageo PLC	Compass Group PLC	Daily Mail & General Trust PLC
Diageo PLC	Diageo PLC	Dixons Retail Group Ltd	Corus Group Ltd	Diageo PLC
Dixons Retail Group Ltd	Dixons Retail Group Ltd	Exel Ltd	Daily Mail & General Trust PLC	Dixons Retail Group Ltd
Electrocomponents PLC	Exel Ltd	Experian Finance PLC	Diageo PLC	EI Group PLC
EMI Group Ltd	Experian Finance PLC	Friends Life FPG Ltd	Dixons Retail Group Ltd	Experian Finance PLC
Experian Finance PLC	Friends Life FPG Ltd	Gallaher Group Ltd	EI Group PLC	Friends Life FPG Ltd
Friends Life FPG Ltd	Gallaher Group Ltd	Gates Worldwide Ltd	Exel Ltd	Gallaher Group Ltd
Gallaher Group Ltd	Gates Worldwide Ltd	GE Healthcare Ltd	Experian Finance PLC	GlaxoSmithKline PLC
GE Healthcare Ltd	GE Healthcare Ltd	GKN PLC	Friends Life FPG Ltd	Hammerson PLC
GlaxoSmithKline PLC	GKN PLC	GlaxoSmithKline PLC	Gallaher Group Ltd	Hanson Ltd
Granada Ltd	GlaxoSmithKline PLC	Granada Ltd	GlaxoSmithKline PLC	HBOS PLC
Hanson Ltd	Granada Ltd	Hanson Ltd	Hanson Ltd	Hibu plc
Hays PLC	Hanson Ltd	Hays PLC	Hays PLC	HSBC Holdings PLC
HBOS PLC	Hays PLC	HBOS PLC	HBOS PLC	Imperial Brands PLC
HSBC Holdings PLC	HBOS PLC	Hibu plc	Hibu plc	Imperial Chemical Industries Ltd
Imperial Brands PLC	HSBC Holdings PLC	HSBC Holdings PLC	HSBC Holdings PLC	InterContinental Hotels Group PLC
Imperial Chemical Industries Ltd	Imperial Brands PLC	Imperial Brands PLC	Imperial Brands PLC	International Consolidated Airlines Grou
International Consolidated Airlines Grou	Imperial Chemical Industries Ltd	Imperial Chemical Industries Ltd	Imperial Chemical Industries Ltd	International Power Ltd
International Power Ltd	International Consolidated Airlines Grou	InterContinental Hotels Group PLC	InterContinental Hotels Group PLC	Intu Properties PLC
Invensys Ltd	Intu Properties PLC	International Consolidated Airlines Grou	International Consolidated Airlines Grou	Invesco Ltd
Invesco Ltd	Invensys Ltd	Intu Properties PLC	Intu Properties PLC	ITV PLC
J Sainsbury PLC	Invesco Ltd	Invesco Ltd	Invesco Ltd	J Sainsbury PLC
Kingfisher PLC	J Sainsbury PLC	J Sainsbury PLC	ITV PLC	Johnson Matthey PLC
Ladbrokes Coral Group PLC	Johnson Matthey PLC	Johnson Matthey PLC	J Sainsbury PLC	KAZ Minerals PLC
Land Securities Group PLC	Kingfisher PLC	Kingfisher PLC	Johnson Matthey PLC	Kelda Group Ltd
Landmark Mortgages Ltd	Ladbrokes Coral Group PLC	Ladbrokes Coral Group PLC	Kingfisher PLC	Kingfisher PLC
Lattice Group Ltd	Land Securities Group PLC	Land Securities Group PLC	Ladbrokes Coral Group PLC	Ladbrokes Coral Group PLC
Legal & General Group PLC	Landmark Mortgages Ltd	Landmark Mortgages Ltd	Land Securities Group PLC	Land Securities Group PLC
LHR Airports Ltd	Legal & General Group PLC	Legal & General Group PLC	Landmark Mortgages Ltd	Landmark Mortgages Ltd
Lloyds Banking Group PLC	LHR Airports Ltd	LHR Airports Ltd	Legal & General Group PLC	Legal & General Group PLC
Logica Ltd	Lloyds Banking Group PLC	Lloyds Banking Group PLC	LHR Airports Ltd	LHR Airports Ltd
Man Group PLC	Man Group PLC	Man Group PLC	Lloyds Banking Group PLC	Lloyds Banking Group PLC
Marks & Spencer Group PLC	Marks & Spencer Group PLC	Marks & Spencer Group PLC	Man Group PLC	Man Group PLC
National Grid PLC	National Grid PLC	National Grid PLC	Marks & Spencer Group PLC	Marks & Spencer Group PLC
Next PLC	Next PLC	Next PLC	National Grid PLC	National Grid PLC
Old Mutual PLC	Old Mutual PLC	Old Mutual PLC	Next PLC	Next PLC
Pearson PLC	Pearson PLC	Pearson PLC	Old Mutual PLC	Old Mutual PLC
Powergen Ltd	Prudential PLC	Prudential PLC	Pearson PLC	Pearson PLC
Prudential PLC	Reckitt Benckiser Group PLC	Reckitt Benckiser Group PLC	Prudential PLC	Persimmon PLC
Reckitt Benckiser Group PLC	RELX PLC	RELX PLC	Reckitt Benckiser Group PLC	Prudential PLC
RELX PLC	Rentokil Initial PLC	Rentokil Initial PLC	RELX PLC	Reckitt Benckiser Group PLC
Rentokil Initial PLC	Rexam Ltd	Rexam Ltd	Rentokil Initial PLC	RELX PLC
Rio Tinto PLC	Rio Tinto PLC	Rio Tinto PLC	Rexam Ltd	Rentokil Initial PLC
Rolls-Royce Holdings PLC	Rolls-Royce Holdings PLC	Rolls-Royce Holdings PLC	Rio Tinto PLC	Rexam Ltd
Royal Bank of Scotland Group PLC	Royal Bank of Scotland Group PLC	Royal Bank of Scotland Group PLC	Rolls-Royce Holdings PLC	Rio Tinto PLC
RSA Insurance Group PLC	RSA Insurance Group PLC	RSA Insurance Group PLC	Royal Bank of Scotland Group PLC	Rolls-Royce Holdings PLC
SABMiller PLC	SABMiller PLC	SABMiller PLC	RSA Insurance Group PLC	Royal Bank of Scotland Group PLC
Safeway Ltd	Safeway Ltd	Safeway Ltd	SABMiller PLC	Royal Dutch Shell PLC
Sage Group PLC/The	Sage Group PLC/The	Sage Group PLC/The	Sage Group PLC/The	RSA Insurance Group PLC
Santander UK PLC	Santander UK PLC	Santander UK PLC	Schroders PLC	SABMiller PLC
Schroders PLC	Schroders PLC	Schroders PLC	Scottish & Newcastle Ltd	Sage Group PLC/The
Scottish & Newcastle Ltd	Scottish & Newcastle Ltd	Scottish & Newcastle Ltd	Scottish Power Ltd	Schroders PLC
Scottish Power Ltd	Scottish Power Ltd	Scottish Power Ltd	Severn Trent PLC	Scottish & Newcastle Ltd
Severn Trent PLC	Severn Trent PLC	Severn Trent PLC	Shell Transport & Trading Co Ltd/The	Scottish Power Ltd
Shell Transport & Trading Co Ltd/The	Shell Transport & Trading Co Ltd/The	Shell Transport & Trading Co Ltd/The	Shire PLC	Severn Trent PLC
Shire PLC	Shire PLC	Shire PLC	Sky PLC	Shire PLC
Six Continents Ltd	Six Continents Ltd	Sky PLC	Smith & Nephew PLC	Sky PLC
Sky PLC	Sky PLC	Smith & Nephew PLC	Smiths Group PLC	Smith & Nephew PLC
Smith & Nephew PLC	Smith & Nephew PLC	Smiths Group PLC	SSE PLC	Smiths Group PLC
Smiths Group PLC	Smiths Group PLC	SSE PLC	Standard Chartered PLC	SSE PLC
SSE PLC	SSE PLC	Standard Chartered PLC	Tate & Lyle PLC	Standard Chartered PLC
Standard Chartered PLC	Standard Chartered PLC	Telefonica Europe PLC	Telefonica Europe PLC	Tate & Lyle PLC
Telefonica Europe PLC	Telefonica Europe PLC	Tesco PLC	Tesco PLC	Telefonica Europe PLC
Tesco PLC	Tesco PLC	Thomson Reuters UK Ltd	Thomson Reuters UK Ltd	Tesco PLC
Thomson Reuters UK Ltd	Thomson Reuters UK Ltd	Unilever PLC	Unilever PLC	Thomson Reuters UK Ltd
Unilever PLC	Unilever PLC	United Utilities Group PLC	United Utilities Group PLC	Unilever PLC
United Utilities Group PLC	United Utilities Group PLC	Vodafone Group PLC	Vodafone Group PLC	United Utilities Group PLC
Vodafone Group PLC	Vodafone Group PLC	Whitbread PLC	Whitbread PLC	Vodafone Group PLC
Wm Morrison Supermarkets PLC	Whitbread PLC	Wm Morrison Supermarkets PLC	William Hill PLC	Wm Morrison Supermarkets PLC
Wolseley PLC	Wm Morrison Supermarkets PLC	Wolseley PLC	Wm Morrison Supermarkets PLC	Wolseley PLC
WPP PLC	Wolseley PLC	WPP PLC	Wolseley PLC	WPP PLC

01/01/2007	01/01/2008	01/01/2009	01/01/2010	01/01/2011
3i Group PLC	3i Group PLC	3i Group PLC	3i Group PLC	3i Group PLC
Alliance & Leicester Ltd	Admiral Group PLC	Admiral Group PLC	Admiral Group PLC	Acacia Mining PLC
Alliance Boots Holdings Ltd	Alliance & Leicester Ltd	Alliance Trust PLC	Aggreko PLC	Admiral Group PLC
Anglo American PLC	Amec Foster Wheeler PLC	Amec Foster Wheeler PLC	Alliance Trust PLC	Aggreko PLC
Antofagasta PLC	Anglo American PLC	Anglo American PLC	Amec Foster Wheeler PLC	Alliance Trust PLC
Associated British Foods PLC	Antofagasta PLC	Antofagasta PLC	Anglo American PLC	Amec Foster Wheeler PLC
AstraZeneca PLC	Associated British Foods PLC	Associated British Foods PLC	Antofagasta PLC	Anglo American PLC
Aviva PLC	AstraZeneca PLC	AstraZeneca PLC	Associated British Foods PLC	Antofagasta PLC
BAE Systems PLC	Aviva PLC	Autonomy Corp Ltd	AstraZeneca PLC	ARM Holdings PLC
Barclays PLC	BAE Systems PLC	Aviva PLC	Autonomy Corp Ltd	Associated British Foods PLC
BG Group Ltd	Barclays PLC	BAE Systems PLC	Aviva PLC	AstraZeneca PLC
BHP Billiton PLC	BG Group Ltd	Barclays PLC	BAE Systems PLC	Autonomy Corp Ltd
BP PLC	BHP Billiton PLC	BG Group Ltd	Barclays PLC	Aviva PLC
Bradford & Bingley PLC	BP PLC	BHP Billiton PLC	BG Group Ltd	BAE Systems PLC
British American Tobacco PLC	British American Tobacco PLC	BP PLC	BHP Billiton PLC	Barclays PLC
British Land Co PLC/The	British Land Co PLC/The	British American Tobacco PLC	BP PLC	BG Group Ltd
BT Group PLC	BT Group PLC	British Land Co PLC/The	British American Tobacco PLC	BHP Billiton PLC
Cable & Wireless Communications Ltd	Cable & Wireless Communications Ltd	BT Group PLC	British Land Co PLC/The	BP PLC
Cadbury Ltd	Cadbury Ltd	Bunzl PLC	BT Group PLC	British American Tobacco PLC
Cairn Energy PLC	Cairn Energy PLC	Cable & Wireless Communications Ltd	Bunzl PLC	British Land Co PLC/The
Capita PLC	Capita PLC	Cadbury Ltd	Burberry Group PLC	BT Group PLC
Carnival PLC	Carnival PLC	Cairn Energy PLC	Cable & Wireless Communications Ltd	Bunzl PLC
Centrica PLC	Carphone Warehouse Group PLC\Old	Capita PLC	Cadbury Ltd	Burberry Group PLC
Compass Group PLC	Centrica PLC	Carnival PLC	Cairn Energy PLC	Cairn Energy PLC
Corus Group Ltd	Compass Group PLC	Centrica PLC	Capita PLC	Capita PLC
Diageo PLC	Diageo PLC	Cobham PLC	Carnival PLC	Carnival PLC
Dixons Retail Group Ltd	EDF Energy Nuclear Generation Group Ltd	Compass Group PLC	Centrica PLC	Centrica PLC
Drax Group PLC	EI Group PLC	Diageo PLC	Cobham PLC	Compass Group PLC
EI Group PLC	Experian PLC	Drax Group PLC	Compass Group PLC	Diageo PLC
Experian PLC	Firstgroup PLC	EDF Energy Nuclear Generation Group Ltd	Diageo PLC	Essar Energy Ltd
Friends Life FPG Ltd	Friends Life FPG Ltd	Eurasian Natural Resources Corp Ltd	Eurasian Natural Resources Corp Ltd	Eurasian Natural Resources Corp Ltd
Gallaher Group Ltd	G4S PLC	Experian PLC	Experian PLC	Experian PLC
GlaxoSmithKline PLC	GlaxoSmithKline PLC	Firstgroup PLC	Fresnillo PLC	Fresnillo PLC
Hammerson PLC	Hammerson PLC	Friends Life FPG Ltd	Friends Life Group Ltd	Friends Life Group Ltd
Hanson Ltd	HBOS PLC	G4S PLC	G4S PLC	G4S PLC
HBOS PLC	Hibu plc	GlaxoSmithKline PLC	GlaxoSmithKline PLC	GKN PLC
Hibu plc	Home Retail Group PLC	Hammerson PLC	Hammerson PLC	GlaxoSmithKline PLC
Home Retail Group PLC	HSBC Holdings PLC	HBOS PLC	Home Retail Group PLC	Hammerson PLC
HSBC Holdings PLC	ICAP PLC	Home Retail Group PLC	HSBC Holdings PLC	HSBC Holdings PLC
ICAP PLC	Imperial Brands PLC	HSBC Holdings PLC	ICAP PLC	ICAP PLC
Imperial Brands PLC	InterContinental Hotels Group PLC	ICAP PLC	Imperial Brands PLC	IMI PLC
Imperial Chemical Industries Ltd	International Consolidated Airlines Grou	Imperial Brands PLC	Inmarsat PLC	Imperial Brands PLC
InterContinental Hotels Group PLC	International Power Ltd	Inmarsat PLC	InterContinental Hotels Group PLC	Inmarsat PLC
International Consolidated Airlines Grou	Intu Properties PLC	InterContinental Hotels Group PLC	International Consolidated Airlines Grou	InterContinental Hotels Group PLC
International Power Ltd	ITV PLC	International Consolidated Airlines Grou	International Power Ltd	International Consolidated Airlines Grou
Intu Properties PLC	J Sainsbury PLC	International Power Ltd	Intertek Group PLC	International Power Ltd
Invesco Ltd	Johnson Matthey PLC	Intu Properties PLC	Intu Properties PLC	Intertek Group PLC
ITV PLC	KAZ Minerals PLC	Invensys Ltd	Invensys Ltd	Intu Properties PLC
J Sainsbury PLC	Kelda Group Ltd	J Sainsbury PLC	J Sainsbury PLC	Invensys Ltd
Johnson Matthey PLC	Kingfisher PLC	Johnson Matthey PLC	Johnson Matthey PLC	Investec PLC
KAZ Minerals PLC	Land Securities Group PLC	KAZ Minerals PLC	KAZ Minerals PLC	J Sainsbury PLC
Kelda Group Ltd	Legal & General Group PLC	Kingfisher PLC	Kingfisher PLC	Johnson Matthey PLC
Kingfisher PLC	Lloyds Banking Group PLC	Land Securities Group PLC	Land Securities Group PLC	KAZ Minerals PLC
Land Securities Group PLC	London Stock Exchange Group PLC	Legal & General Group PLC	Legal & General Group PLC	Kingfisher PLC
Landmark Mortgages Ltd	Lonmin PLC	Lloyds Banking Group PLC	Lloyds Banking Group PLC	Land Securities Group PLC
Legal & General Group PLC	Man Group PLC	London Stock Exchange Group PLC	London Stock Exchange Group PLC	Legal & General Group PLC
Lloyds Banking Group PLC	Marks & Spencer Group PLC	Man Group PLC	Lonmin PLC	Lloyds Banking Group PLC
Lonmin PLC	National Grid PLC	Marks & Spencer Group PLC	Man Group PLC	Lonmin PLC
Man Group PLC	Next PLC	MS Amlin PLC	Marks & Spencer Group PLC	Man Group PLC
Marks & Spencer Group PLC	Old Mutual PLC	National Grid PLC	National Grid PLC	Marks & Spencer Group PLC
National Grid PLC	Pearl Group Holdings No 1 Ltd	Next PLC	Next PLC	National Grid PLC
Next PLC	Pearson PLC	Old Mutual PLC	Old Mutual PLC	Next PLC
Old Mutual PLC	Persimmon PLC	Pearson PLC	Pearson PLC	Old Mutual PLC
Pearl Group Holdings No 1 Ltd	Prudential PLC	Prudential PLC	Petrofac Ltd	Pearson PLC
Pearson PLC	Reckitt Benckiser Group PLC	Randgold Resources Ltd	Prudential PLC	Petrofac Ltd
Persimmon PLC	RELX PLC	Reckitt Benckiser Group PLC	Randgold Resources Ltd	Prudential PLC
Prudential PLC	Rentokil Initial PLC	RELX PLC	Reckitt Benckiser Group PLC	Randgold Resources Ltd
Reckitt Benckiser Group PLC	Rexam Ltd	Rexam Ltd	RELX PLC	Reckitt Benckiser Group PLC
RELX PLC	Rio Tinto PLC	Rio Tinto PLC	Rexam Ltd	RELX PLC
Rexam Ltd	Rolls-Royce Holdings PLC	Rolls-Royce Holdings PLC	Rio Tinto PLC	Rexam Ltd
Rio Tinto PLC	Royal Bank of Scotland Group PLC	Royal Bank of Scotland Group PLC	Rolls-Royce Holdings PLC	Rio Tinto PLC
Rolls-Royce Holdings PLC	Royal Dutch Shell PLC	Royal Dutch Shell PLC	Royal Bank of Scotland Group PLC	Rolls-Royce Holdings PLC
Royal Bank of Scotland Group PLC	RSA Insurance Group PLC	RSA Insurance Group PLC	Royal Dutch Shell PLC	Royal Bank of Scotland Group PLC
Royal Dutch Shell PLC	SABMiller PLC	SABMiller PLC	RSA Insurance Group PLC	Royal Dutch Shell PLC
RSA Insurance Group PLC	Sage Group PLC/The	Sage Group PLC/The	SABMiller PLC	RSA Insurance Group PLC
SABMiller PLC	Schroders PLC	Schroders PLC	Sage Group PLC/The	SABMiller PLC
Sage Group PLC/The	Scottish & Newcastle Ltd	Serco Group PLC	Schroders PLC	Sage Group PLC/The
Scottish & Newcastle Ltd	Severn Trent PLC	Severn Trent PLC	Segro PLC	Schroders PLC
Scottish Power Ltd	Shire PLC	Shire PLC	Serco Group PLC	Serco Group PLC
Segro PLC	Sky PLC	Sky PLC	Severn Trent PLC	Severn Trent PLC
Severn Trent PLC	Smith & Nephew PLC	Smith & Nephew PLC	Shire PLC	Shire PLC
Shire PLC	Smiths Group PLC	Smiths Group PLC	Sky PLC	Sky PLC
Sky PLC	SSE PLC	SSE PLC	Smith & Nephew PLC	Smith & Nephew PLC
Smith & Nephew PLC	Standard Chartered PLC	Standard Chartered PLC	Smiths Group PLC	Smiths Group PLC
Smiths Group PLC	Standard Life PLC	Standard Life PLC	SSE PLC	SSE PLC
SSE PLC	Taylor Wimpey PLC	Tate & Lyle PLC	Standard Chartered PLC	Standard Chartered PLC
Standard Chartered PLC	Tesco PLC	Tesco PLC	Standard Life PLC	Standard Life PLC
Standard Life PLC	Thomas Cook Group PLC	Thomas Cook Group PLC	Tesco PLC	Tesco PLC
Tate & Lyle PLC	Thomson Reuters UK Ltd	Thomson Reuters UK Ltd	Thomas Cook Group PLC	TUI Travel Ltd
Tesco PLC	TUI Travel Ltd	TUI Travel Ltd	TUI Travel Ltd	Tullow Oil PLC
Thomson Reuters UK Ltd	Tullow Oil PLC	Tullow Oil PLC	Tullow Oil PLC	Unilever PLC
Unilever PLC	Unilever PLC	Unilever PLC	Unilever PLC	United Utilities Group PLC
United Utilities Group PLC	United Utilities Group PLC	United Utilities Group PLC	United Utilities Group PLC	Vedanta Resources PLC
Vedanta Resources PLC	Vedanta Resources PLC	Vedanta Resources PLC	Vedanta Resources PLC	Vodafone Group PLC
Vodafone Group PLC	Vodafone Group PLC	Vodafone Group PLC	Vodafone Group PLC	Weir Group PLC/The
Whitbread PLC	Whitbread PLC	Whitbread PLC	Whitbread PLC	Whitbread PLC
Wm Morrison Supermarkets PLC	Wm Morrison Supermarkets PLC	Wm Morrison Supermarkets PLC	Wm Morrison Supermarkets PLC	Wm Morrison Supermarkets PLC
Wolseley PLC	Wolseley PLC	Wolseley PLC	Wolseley PLC	Wolseley PLC

01/01/2012	01/01/2013	01/01/2014	01/01/2015	01/01/2016
Admiral Group PLC	Aberdeen Asset Management PLC	Aberdeen Asset Management PLC	3i Group PLC	3i Group PLC
Aggreko PLC	Admiral Group PLC	Admiral Group PLC	Aberdeen Asset Management PLC	Aberdeen Asset Management PLC
Amec Foster Wheeler PLC	Aggreko PLC	Aggreko PLC	Admiral Group PLC	Admiral Group PLC
Anglo American PLC	Amec Foster Wheeler PLC	Amec Foster Wheeler PLC	Aggreko PLC	Anglo American PLC
Antofagasta PLC	Anglo American PLC	Anglo American PLC	Anglo American PLC	Antofagasta PLC
ARM Holdings PLC	Antofagasta PLC	Antofagasta PLC	Antofagasta PLC	ARM Holdings PLC
Ashmore Group PLC	ARM Holdings PLC	ARM Holdings PLC	ARM Holdings PLC	Ashtead Group PLC
Associated British Foods PLC	Associated British Foods PLC	Ashtead Group PLC	Ashtead Group PLC	Associated British Foods PLC
AstraZeneca PLC	AstraZeneca PLC	Associated British Foods PLC	Associated British Foods PLC	AstraZeneca PLC
Aviva PLC	Aviva PLC	AstraZeneca PLC	AstraZeneca PLC	Aviva PLC
BAE Systems PLC	Babcock International Group PLC	Aviva PLC	Aviva PLC	Babcock International Group PLC
Barclays PLC	BAE Systems PLC	Babcock International Group PLC	Babcock International Group PLC	BAE Systems PLC
BG Group Ltd	Barclays PLC	BAE Systems PLC	BAE Systems PLC	Barclays PLC
BHP Billiton PLC	BG Group Ltd	Barclays PLC	Barclays PLC	Barratt Developments PLC
BP PLC	BHP Billiton PLC	BG Group Ltd	Barratt Developments PLC	Berkeley Group Holdings PLC
British American Tobacco PLC	BP PLC	BHP Billiton PLC	BG Group Ltd	BG Group Ltd
British Land Co PLC/The	British American Tobacco PLC	BP PLC	BHP Billiton PLC	BHP Billiton PLC
BT Group PLC	British Land Co PLC/The	British American Tobacco PLC	BP PLC	BP PLC
Bunzl PLC	BT Group PLC	British Land Co PLC/The	British American Tobacco PLC	British American Tobacco PLC
Burberry Group PLC	Bunzl PLC	BT Group PLC	British Land Co PLC/The	British Land Co PLC/The
Cairn Energy PLC	Burberry Group PLC	Bunzl PLC	BT Group PLC	BT Group PLC
Capita PLC	Capita PLC	Burberry Group PLC	Bunzl PLC	Bunzl PLC
Carnival PLC	Carnival PLC	Capita PLC	Burberry Group PLC	Burberry Group PLC
Centrica PLC	Centrica PLC	Carnival PLC	Capita PLC	Capita PLC
Compass Group PLC	Compass Group PLC	Centrica PLC	Carnival PLC	Carnival PLC
CRH PLC	CRH PLC	Coca-Cola HBC AG	Centrica PLC	Centrica PLC
Diageo PLC	Croda International PLC	Compass Group PLC	Coca-Cola HBC AG	Coca-Cola HBC AG
Essar Energy Ltd	Diageo PLC	CRH PLC	Compass Group PLC	Compass Group PLC
Eurasian Natural Resources Corp Ltd	Eurasian Natural Resources Corp Ltd	Diageo PLC	CRH PLC	CRH PLC
Evraz PLC	Evraz PLC	easyJet PLC	Diageo PLC	DCC PLC
Experian PLC	Experian PLC	Experian PLC	Direct Line Insurance Group PLC	Diageo PLC
Fresnillo PLC	Fresnillo PLC	Fresnillo PLC	Dixons Carphone PLC	Direct Line Insurance Group PLC
Friends Life Group Ltd	Friends Life Group Ltd	Friends Life Group Ltd	easyJet PLC	Dixons Carphone PLC
G4S PLC	G4S PLC	G4S PLC	Experian PLC	easyJet PLC
GKN PLC	GKN PLC	GKN PLC	Fresnillo PLC	Experian PLC
GlaxoSmithKline PLC	GlaxoSmithKline PLC	GlaxoSmithKline PLC	Friends Life Group Ltd	Fresnillo PLC
Glencore PLC	Glencore PLC	Glencore PLC	G4S PLC	GKN PLC
Hammerson PLC	Hammerson PLC	Hammerson PLC	GKN PLC	GlaxoSmithKline PLC
Hargreaves Lansdown PLC	Hargreaves Lansdown PLC	Hargreaves Lansdown PLC	GlaxoSmithKline PLC	Glencore PLC
HSBC Holdings PLC	HSBC Holdings PLC	HSBC Holdings PLC	Glencore PLC	Hammerson PLC
ICAP PLC	IMI PLC	IMI PLC	Hammerson PLC	Hargreaves Lansdown PLC
IMI PLC	Imperial Brands PLC	Imperial Brands PLC	Hargreaves Lansdown PLC	Hikma Pharmaceuticals PLC
Imperial Brands PLC	InterContinental Hotels Group PLC	InterContinental Hotels Group PLC	HSBC Holdings PLC	HSBC Holdings PLC
InterContinental Hotels Group PLC	International Consolidated Airlines Grou	International Consolidated Airlines Grou	Imperial Brands PLC	Imperial Brands PLC
International Consolidated Airlines Grou	Intertek Group PLC	Intertek Group PLC	InterContinental Hotels Group PLC	Inmarsat PLC
International Power Ltd	Intu Properties PLC	ITV PLC	International Consolidated Airlines Grou	InterContinental Hotels Group PLC
Intertek Group PLC	ITV PLC	J Sainsbury PLC	Intertek Group PLC	International Consolidated Airlines Grou
Intu Properties PLC	J Sainsbury PLC	Johnson Matthey PLC	Intu Properties PLC	Intertek Group PLC
ITV PLC	John Wood Group PLC	Kingfisher PLC	ITV PLC	Intu Properties PLC
J Sainsbury PLC	Johnson Matthey PLC	Land Securities Group PLC	J Sainsbury PLC	ITV PLC
Johnson Matthey PLC	KAZ Minerals PLC	Legal & General Group PLC	Johnson Matthey PLC	J Sainsbury PLC
KAZ Minerals PLC	Kingfisher PLC	Lloyds Banking Group PLC	Kingfisher PLC	Johnson Matthey PLC
Kingfisher PLC	Land Securities Group PLC	London Stock Exchange Group PLC	Land Securities Group PLC	Kingfisher PLC
Land Securities Group PLC	Legal & General Group PLC	Marks & Spencer Group PLC	Legal & General Group PLC	Land Securities Group PLC
Legal & General Group PLC	Lloyds Banking Group PLC	Meggitt PLC	Lloyds Banking Group PLC	Legal & General Group PLC
Lloyds Banking Group PLC	Marks & Spencer Group PLC	Melrose Industries PLC	London Stock Exchange Group PLC	Lloyds Banking Group PLC
Man Group PLC	Meggitt PLC	Mondi PLC	Marks & Spencer Group PLC	London Stock Exchange Group PLC
Marks & Spencer Group PLC	Melrose Industries PLC	National Grid PLC	Meggitt PLC	Marks & Spencer Group PLC
Meggitt PLC	National Grid PLC	Next PLC	Mondi PLC	Merlin Entertainments PLC
National Grid PLC	Next PLC	Old Mutual PLC	National Grid PLC	Mondi PLC
Next PLC	Old Mutual PLC	Pearson PLC	Next PLC	National Grid PLC
Old Mutual PLC	Pearson PLC	Persimmon PLC	Old Mutual PLC	Next PLC
Pearson PLC	Petrofac Ltd	Petrofac Ltd	Pearson PLC	Old Mutual PLC
Petrofac Ltd	Polymetal International PLC	Prudential PLC	Persimmon PLC	Pearson PLC
Polymetal International PLC	Prudential PLC	Randgold Resources Ltd	Prudential PLC	Persimmon PLC
Prudential PLC	Randgold Resources Ltd	Reckitt Benckiser Group PLC	Randgold Resources Ltd	Provident Financial PLC
Randgold Resources Ltd	Reckitt Benckiser Group PLC	RELX PLC	Reckitt Benckiser Group PLC	Prudential PLC
Reckitt Benckiser Group PLC	RELX PLC	Rexam Ltd	RELX PLC	Randgold Resources Ltd
RELX PLC	Rexam Ltd	Rio Tinto PLC	Rio Tinto PLC	Reckitt Benckiser Group PLC
Rexam Ltd	Rio Tinto PLC	Rolls-Royce Holdings PLC	Rolls-Royce Holdings PLC	RELX PLC
Rio Tinto PLC	Rolls-Royce Holdings PLC	Royal Bank of Scotland Group PLC	Royal Bank of Scotland Group PLC	Rio Tinto PLC
Rolls-Royce Holdings PLC	Royal Bank of Scotland Group PLC	Royal Dutch Shell PLC	Royal Dutch Shell PLC	Rolls-Royce Holdings PLC
Royal Bank of Scotland Group PLC	Royal Dutch Shell PLC	Royal Mail PLC	Royal Mail PLC	Royal Bank of Scotland Group PLC
Royal Dutch Shell PLC	RSA Insurance Group PLC	RSA Insurance Group PLC	RSA Insurance Group PLC	Royal Dutch Shell PLC
RSA Insurance Group PLC	SABMiller PLC	SABMiller PLC	SABMiller PLC	Royal Mail PLC
SABMiller PLC	Sage Group PLC/The	Sage Group PLC/The	Sage Group PLC/The	RSA Insurance Group PLC
Sage Group PLC/The	Schroders PLC	Schroders PLC	Schroders PLC	SABMiller PLC
Schroders PLC	Serco Group PLC	Severn Trent PLC	Severn Trent PLC	Sage Group PLC/The
Serco Group PLC	Severn Trent PLC	Shire PLC	Shire PLC	Schroders PLC
Severn Trent PLC	Shire PLC	Sky PLC	Sky PLC	Severn Trent PLC
Shire PLC	Sky PLC	Smith & Nephew PLC	Smith & Nephew PLC	Shire PLC
Sky PLC	Smith & Nephew PLC	Smiths Group PLC	Smiths Group PLC	Sky PLC
Smith & Nephew PLC	Smiths Group PLC	Sports Direct International PLC	Sports Direct International PLC	Smith & Nephew PLC
Smiths Group PLC	SSE PLC	SSE PLC	SSE PLC	Smiths Group PLC
SSE PLC	Standard Chartered PLC	Standard Chartered PLC	St James's Place PLC	Sports Direct International PLC
Standard Chartered PLC	Standard Life PLC	Standard Life PLC	Standard Chartered PLC	SSE PLC
Standard Life PLC	Tate & Lyle PLC	Tate & Lyle PLC	Standard Life PLC	St James's Place PLC
Tate & Lyle PLC	Tesco PLC	Tesco PLC	Taylor Wimpey PLC	Standard Chartered PLC
Tesco PLC	TUI Travel Ltd	Travis Perkins PLC	Tesco PLC	Standard Life PLC
Tullow Oil PLC	Tullow Oil PLC	TUI Travel Ltd	Travis Perkins PLC	Taylor Wimpey PLC
Unilever PLC	Unilever PLC	Tullow Oil PLC	TUI AG	Tesco PLC
United Utilities Group PLC	United Utilities Group PLC	Unilever PLC	Tullow Oil PLC	Travis Perkins PLC
Vedanta Resources PLC	Vedanta Resources PLC	United Utilities Group PLC	Unilever PLC	TUI AG
Vodafone Group PLC	Vodafone Group PLC	Vodafone Group PLC	United Utilities Group PLC	Unilever PLC
Weir Group PLC/The	Weir Group PLC/The	Weir Group PLC/The	Vodafone Group PLC	United Utilities Group PLC
Whitbread PLC	Whitbread PLC	Whitbread PLC	Weir Group PLC/The	Vodafone Group PLC
Wm Morrison Supermarkets PLC	Wm Morrison Supermarkets PLC	William Hill PLC	Whitbread PLC	Whitbread PLC
Wolseley PLC	Wolseley PLC	Wm Morrison Supermarkets PLC	Wm Morrison Supermarkets PLC	Wolseley PLC

C - Portfolio Performance

Table 17: Overview over FTSE 100 and DoD portfolio performance for the period 2002 - 2016

	2002		2003		2004		2005		2006		2007		2008	
Month	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**
Jan	9,899	9,968	6,838	6,771	8,415	9,409	9,300	11,911	11,041	14,741	11,889	20,325	11,270	20,596
Feb	9,777	9,693	7,007	6,425	8,610	10,163	9,523	12,355	11,100	15,558	11,829	19,930	11,278	19,419
Mar	10,065	10,315	6,925	6,363	8,406	9,980	9,381	12,394	11,432	15,709	12,090	20,970	10,929	18,677
Apr	9,901	10,282	7,525	7,311	8,605	10,100	9,203	12,261	11,544	15,585	12,361	21,547	11,667	18,513
May	9,746	10,419	7,759	8,134	8,477	10,268	9,514	12,878	10,971	15,930	12,691	22,336	11,603	18,059
Jun	8,925	9,412	7,726	8,140	8,556	10,627	9,800	13,142	11,181	16,730	12,665	21,889	10,783	15,395
Jul	8,139	8,779	7,968	8,563	8,458	10,453	10,124	13,080	11,363	17,457	12,190	20,732	10,373	14,916
Aug	8,102	8,826	7,975	8,773	8,547	10,538	10,152	13,110	11,320	18,037	12,081	21,414	10,803	16,643
Sept	7,133	7,903	7,842	8,321	8,761	10,896	10,499	13,511	11,425	18,876	12,395	21,946	9,396	15,081
Oct	7,743	8,294	8,218	8,962	8,863	11,183	10,191	13,217	11,748	19,388	12,883	22,686	8,390	12,281
Nov	7,991	7,930	8,323	9,160	9,014	11,273	10,394	13,750	11,594	19,817	12,329	22,293	8,219	12,629
Dec	7,552	7,495	8,581	9,356	9,227	11,872	10,769	14,642	11,923	20,506	12,376	22,164	8,499	13,894
Return	**-28.07%**	**-28.84%**	**12.76%**	**22.18%**	**7.27%**	**23.82%**	**15.45%**	**20.97%**	**10.18%**	**33.68%**	**3.73%**	**7.77%**	**-37.58%**	**-46.70%**

	2009		2010		2011		2012		2013		2014		2015		2016	
Month	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**	**FTSE 100**	**DoD**
Jan	7,953	12,064	9,945	17,462	11,237	19,905	10,890	21,118	12,031	24,676	12,478	27,999	12,936	30,084	11,661	27,237
Feb	7,341	10,966	10,263	17,396	11,489	20,558	11,254	22,352	12,192	24,605	13,052	28,164	13,314	30,637	11,686	29,742
Mar	7,525	12,279	10,886	17,910	11,325	20,409	11,056	22,588	12,440	24,969	12,647	27,484	12,982	29,982	11,835	31,198
Apr	8,134	15,159	10,644	18,143	11,659	21,422	10,997	21,908	12,324	25,751	12,995	28,309	13,341	31,426	11,964	34,254
May	8,468	14,205	9,896	17,559	11,481	21,515	10,198	20,628	12,618	26,816	13,119	29,222	13,387	31,876	11,942	32,785
Jun	8,144	15,110	9,424	17,760	11,396	21,336	10,678	21,599	11,913	26,154	12,926	28,695	12,499	29,887	12,467	35,735
Jul	8,833	16,707	10,078	18,682	11,146	20,924	10,801	21,947	12,690	28,341	12,899	28,884	12,835	30,249	12,888	36,487
Aug	9,238	18,270	10,015	18,680	10,339	20,181	10,947	22,663	12,291	27,674	13,071	29,165	11,612	28,598	12,998	37,071
Sept	9,840	18,212	10,635	18,820	9,830	20,160	11,006	23,175	12,386	28,054	12,694	28,216	11,618	27,859	13,224	39,418
Oct	9,669	17,388	10,877	19,878	10,626	20,769	11,083	23,459	12,902	29,388	12,547	28,694	12,192	29,136	13,329	41,802
Nov	9,949	17,941	10,596	19,145	10,552	21,183	11,245	23,342	12,747	28,366	12,885	29,829	12,182	28,783	13,002	41,265
Dec	10,375	17,991	11,308	20,048	10,680	21,111	11,304	23,832	12,936	27,934	12,585	29,481	11,964	28,317	13,690	43,100
Return	**19.94%**	**25.84%**	**8.62%**	**10.83%**	**-5.71%**	**5.16%**	**5.68%**	**12.12%**	**13.48%**	**15.88%**	**-2.75%**	**5.39%**	**-5.06%**	**-4.03%**	**13.48%**	**42.01%**

D - Python Code

D.1 Part 1

This is the main code:

```
# In[1]:


get_ipython().magic('matplotlib inline')
#%% Preamp
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all" # For reference, the options for that are
↪  'all', 'none', 'last' and 'last_expr'

import seaborn as sns
import numpy as np
import pandas as pd
pd.options.display.float_format = '{:,.5f}'.format

import matplotlib.pyplot as plt
from matplotlib import style
style.use('seaborn-whitegrid')
#print(plt.style.available)
import matplotlib.ticker as mtick
import matplotlib.dates as mdates
import matplotlib.mlab as mlab
from matplotlib.ticker import FuncFormatter

import statsmodels.api as sm
```

```
import statsmodels.tools

from scipy import stats
import time


# # Importing data

# In[2]:

start = time.time()
#import data_to_pickle # Used to import data and read into pickles
# Read pickles
import read_pickle as pick
import functions as func

# Organisation of data
# Here, I organise all the stock prices into the possible investment universes.
# This is done by constructing a dictionary

universe = {}
for i in range(0,len(pick.investmentuniverse.columns)):
    universe [str(i)] =
     ↪ pick.investmentuniverse[pick.investmentuniverse.columns[i]].dropna()
    # Dropna to filter out any missing values

Portfolios = {}
years = []
for i in range (2002, 2016+1):
    years.append(i)
for i in range (2, 17):
    Portfolios [str(i)] = pick.icm[universe[str(i-2)]].loc[str(years[i-2])][1:]

# Dividends
dividends_quarterly = pick.dividends.resample('Q').sum()

# Python file with construction of portfolios
import ICM296_portfolioconstruction as pc # pc = portfolio_constructor

# Risk-free rate
rf = pd.read_pickle('rf')
rf = rf.iloc[:509]
rf = rf / 100
```

```
rf['IUMAJNB'] = rf['IUMAJNB'].map(lambda x: np.log((1+ x * (91/365.25))**(30.4375/91) ))
rf = rf * 100
rf.columns = rf.columns.map(lambda x: x + str(' (%)'))

rf.head()
rf.plot()


# # Regressions

# ## Data Prep

# In[3]:

Benchmark = pick.icm['UKX Index'].copy()
Benchmark = Benchmark.fillna(method = 'bfill')
Benchmark = Benchmark.pct_change(1)+1
Benchmark = Benchmark.iloc[1:]
Benchmark = np.log(Benchmark)*100
Benchmark = Benchmark.resample('M').sum()
Benchmark = Benchmark['2002':'2016']

df = pd.read_pickle('df')
df['Dates'] = pd.DatetimeIndex(freq = 'M', start='2002', end = '2017')
df.set_index('Dates', inplace = True)
df = np.log(df)*100
df['FTSE 100'] = Benchmark
df.columns = ['DoD', 'FTSE 100']
df ['DoD - FTSE 100'] = df['DoD'] - df ['FTSE 100']
df[['PDoD', 'PFTSE 100']]  =  np.exp(df[['DoD','FTSE 100']]/100)
df['PPDoD'] = func.valuecalculator(df['PDoD'])[1:]
Benchmark_value = func.valuecalculator(np.exp(Benchmark/100))[1:]
df['PPFTSE 100'] = Benchmark_value
df.columns = ['DoD (%)', 'FTSE 100 (%)',
              'DoD - FTSE 100 (%)', 'PDoD',
              'PFTSE 100', 'PPDoD', 'PPFTSE 100']
df ['Risk-Free Rate (%)'] = rf.loc['2001-12-30':'2016',:].shift(1).iloc[1:]
# Risk-free rate is shifted one month forward to reflect that the rate is for the next
↪  month

df.tail()
```

```
# ## Data prep

# In[4]:


fama = pd.read_pickle('fama')
fama.set_index(pd.DatetimeIndex(freq = 'M', start='1980-10', end = '2016-7'), inplace =
↪  True)
fama = fama.loc['2002':,:]
fama ['DoD-Rf'] = (df.loc[:'2016-6','DoD (%)'] / 100) - (df.loc[:'2016-6','Risk-Free Rate
↪  (%)'] / 100)
fama ['Rm-Rf'] = (df.loc[:'2016-6','FTSE 100 (%)'] / 100) - (df.loc[:'2016-6','Risk-Free
↪  Rate (%)'] / 100)
fama = fama.loc[:,['DoD-Rf','Rm-Rf','SMB','HML', 'UMD']]

fama.head()


# ## CAPM

# In[5]:


ydata = fama.loc[:,'DoD-Rf']
xdata = fama.loc[:,fama.columns[1]]
CAPM_results = sm.OLS(ydata, sm.add_constant(xdata)).fit()

print(CAPM_results.summary(yname = 'DoD Excess Returns'))


# ### CAPM Plot

# In[6]:


plt.close('all')
sns.set(color_codes=True)
fama.to_clipboard()
ax = sns.regplot(xdata,ydata, scatter = True)
ax.set_facecolor('white')
ax.grid(False)
xaxis = ax.get_xlim()

ax.annotate('Regression line: y = {:.5f} +'
            '{:.3f}x\nR-Square: {:.4f}'.format(CAPM_results.params[0],
                                                CAPM_results.params[1],
```

```
                                              CAPM_results.rsquared),
            (xaxis[0],0.93*ax.get_ylim()[1]))

ax.set_ylim(top = ax.get_ylim()[1]*1.1)
plt.title('CAPM ', loc = 'left', fontweight = 'bold')

plt.axhline(y = 0, color = 'k', linewidth = 0.5)

savepath = 'C:/Users/Christopher/Dropbox/2. ICMA Centre/PROTEXT
↪  test/ICM_296/CAPM_plot.png'
plt.savefig(savepath,transparent = True, dpi = 300, bbox_inches="tight");


# ## Fama French

# In[7]:

ydata = fama.loc[:,'DoD-Rf']
xdata = fama.loc[:,fama.columns[1:-1]]

FF_results = sm.OLS(ydata, sm.add_constant(xdata)).fit()
print(FF_results.summary(yname = 'DoD Excess Returns'));


# ## Carhart

# In[8]:

ydata = fama.loc[:,'DoD-Rf']
xdata = fama.loc[:,fama.columns[1:]]

CAR_results = sm.OLS(ydata, sm.add_constant(xdata)).fit()
print(CAR_results.summary(yname = 'DoD Excess Returns'));


# # Risk Measures

# ## Test Statistics

# In[9]:

series = df.loc[:,'DoD (%)'] - df.loc[:,'Risk-Free Rate (%)']
```

```python
d = series.mean()
s = series.std(ddof = 1)
n = np.sqrt(len((series)))

t = d/s*n

pval = stats.t.sf(np.abs(t), n**2-1)*2 # Must be two-sided as we're looking at <> 0

if pval <= 0.05:
    print('t-statistics = {:.2f}, P-value = {:.3f}'
          ' (Statistically significant)'.format(t, pval))
else:
    print('t-statistics = {:.2f}, P-value = {:.3f}'
          ' (Not statistically significant)'.format(t, pval))


# ## Maximum Drawdown

# In[10]:

# A drawdown is a measurement of decline from an assets peak value to its
# lowest point over a period of time. The drawdown is usually expressed as a
# percentage from top to bottom. It can be measured on any asset including
# individual stocks or sectors. However, it is most valuable as a measurement
# of portfolio risk.
max_drawdownDoD = func.DD_measure(df['PPDoD'])
max_drawdownBench = func.DD_measure(df['PPFTSE 100'])
print("Max DoD drawdown is {:.2f}%".format(max_drawdownDoD))
print("Max benchmark drawdown is {:.2f}%".format(max_drawdownBench))


# ## VaR and Expected Shortfall

# In[11]:

VV = func.VaR (df.loc[:,'DoD (%)']) # Self-made function
VV.head()
VV.loc[:,['DoD (%)','Cumulative Weight']].where(VV['Cumulative Weight'] <= .05).dropna()
VV2 = func.VaR (df.loc[:,'FTSE 100 (%)'])
VV2.loc[:,['FTSE 100 (%)','Cumulative Weight']].where(VV2['Cumulative Weight'] <=
↪  .05).dropna()
```

```
print("The expected shortfall is: ",VV.loc[:,['DoD (%)']].where(VV['Cumulative Weight'] <
↪  .05).dropna().mean())
print("The expected shortfall is: ",VV2.loc[:,['FTSE 100 (%)']].
      where(VV2['Cumulative Weight'] < .05).dropna().mean())


# ## Portfolio Turnover

# In[12]:

lenght = len(np.unique(pick.DoDportfolios.values))
print("\n \nThe number of constituting companies in the DoD is: {}".format(lenght))
DoD = pick.DoDportfolios.copy()

turnover = [0]
for i in range(2002,2016):
    temp = []
    for item in DoD[i]:

        if item in str(DoD[i+1]):
            temp.append(1)
        else:
            temp.append(0)
    turnover.append((10-sum(temp))/10)

turnover_mean = np.mean(turnover[1:])  * 100
transactioncost = 2*turnover_mean*0.01

print('The average turnover in the period 2002 - 2016 '
      'is: {:.3f}%'.format(turnover_mean))
print('Therefore, turnover costs equates to: '
      '{:.2f}%'.format(transactioncost))


# ## Skewness and Kurtosis

# In[13]:

# The bias = False is due to different normalizations.
# Scipy by default does not correct for bias
skew = stats.skew(fama.loc[:,'DoD-Rf'], bias = False)
skew2 = stats.skew(fama.loc[:,'Rm-Rf'], bias = False)
```

```
kurt = stats.kurtosis(fama.loc[:,'DoD-Rf'], bias = False)
kurt2 = stats.kurtosis(fama.loc[:,'Rm-Rf'], bias = False)

print('\n(DoD), (FTSE 100)\n---------------------------'
      '\nSkew: ({:.4f}), ({:.4f})'
      '\nKurtosis: ({:.4f}), ({:.4f})'
      .format(skew, skew2,
             kurt, kurt2))


# ### Jarque-Bera

# In[14]:

semi = (fama.loc[:,'DoD-Rf'])  # DoD portfolio excess returns
semi2 = fama.loc[:,'Rm-Rf'] # FTSE 100 excess returns

S = float(semi.shape[0]) / 6 * (skew**2 + 0.25*((kurt-3)**2)) # Test statistics
t = stats.chi2(2).ppf(0.95) # Threshold level
if S < t:
    print ("Not enough evidence to reject DoD as Normal "
           "according to the Jarque-Bera test. S = {:.4f} < {:.4f}".format(S,t))
else:
    print ("Reject that DoD is Normal according to "
           "the Jarque-Bera test; S = {:.4f} > {:.4f}".format(S,t))

S = float(semi2.shape[0]) / 6 * (skew2**2 + 0.25*((kurt2-3)**2)) # Test statistics
t = stats.chi2(2).ppf(0.95) # Threshold level
if S < t:
    print ("Not enough evidence to reject FTSE 100 as "
           "Normal according to the Jarque-Bera test. S = {:.4f} < {:.4f}".format(S,t))
else:
    print ("Reject that FTSE 100 is Normal according to the "
           "Jarque-Bera test; S = {:.4f} > {:.4f}".format(S,t))



# ## Corr, Variance, STD, SV and SSD

# ### Correlation

# In[15]:
```

```
fama.loc[:,fama.columns[:2]].corr()
fama.loc[:,fama.columns[:2]].cov()*12*100


# ### Variance

# In[16]:

var = np.var(semi, ddof = 1)
var2 = np.var(semi2, ddof = 1)
std = np.std(semi, ddof = 1) * np.sqrt(12) * 100
std2 = np.std(semi2, ddof = 1) * np.sqrt(12) * 100

print('\n(DoD), (FTSE 100)\n----------------------------'
      '\nVariance: ({:.4f}), ({:.4f})'
      '\nStandard Deviation: ({:.4f}), ({:.4f}) *Figures are annualised'
      .format(var, var2,
              std, std2))


# ### Semi-Variance and Semi-Standard Deviation

# In[17]:

# Based on the LPM using the average excess return as minimal acceptable return, the
# concepts of semi-variance (SV) and semi-standard
# deviation (SSD) can be calculated

threshold1 = np.mean(semi)
threshold2 = np.mean(semi2)

semi_variance1 = func.LPM(semi,threshold1,2)
# This is for the DoD porfolio, using the mean as the threshold
semi_variance2 = func.LPM(semi2,threshold2,2)
# This is for the FTSE 100 porfolio, using the mean as the threshold

Semi_std_DoD, Semi_std_Bench = np.sqrt(semi_variance1), np.sqrt(semi_variance2)

print("Semi-variance is {:.3f}% for DoD, and {:.3f}% for FTSE 100".
      format(semi_variance1*100,semi_variance2*100))


# ## Relative Risk Measures
```

```python
# In[18]:

DoD_excess_mean = fama.loc[:,'DoD-Rf'].mean()
Benchmark_excess_mean = fama.loc[:,'Rm-Rf'].mean()
DoD_excess_std = fama.loc[:,'DoD-Rf'].std(ddof = 1)
Benchmark_excess_std = fama.loc[:,'Rm-Rf'].std(ddof = 1)


# ### Sharpe:

# In[19]:

sharpeDoD, sharpeBench = [DoD_excess_mean / DoD_excess_std,
                          Benchmark_excess_mean / Benchmark_excess_std]
sharpeDoD, sharpeBench


# ### RAPA

# In[20]:

RAPA = DoD_excess_mean * Benchmark_excess_std / DoD_excess_std
RAPA


# ### Treynor:

# In[21]:

TreynorDoD, TreynorBench = [DoD_excess_mean / CAR_results.params[1],
                            Benchmark_excess_mean / 1]
# Beta from CARHART regression
TreynorDoD, TreynorBench


# ### Sortino:

# In[22]:

SortinoDoD, SortinoBench = [DoD_excess_mean / Semi_std_DoD,
                            Benchmark_excess_mean / Semi_std_Bench]
```

```
# ### Probability of Shortfall and Return on Probability of Shortfall

# In[23]:

prob_of_shortfallDoD = func.LPM(semi, threshold1,0)
prob_of_shortfallBench = func.LPM(semi2, threshold2,0)
return_on_probability_shortfallDoD = DoD_excess_mean / prob_of_shortfallDoD
return_on_probability_shortfallBench = Benchmark_excess_mean / prob_of_shortfallBench


# ## Summary

# In[24]:

#%% Arithmetic returns
test = pd.DataFrame(df.loc[:,df.columns[0]]/100)


test ['RF'] = rf.loc['2002':'2016','IUMAJNB (%)']/100
test = test.loc['2002':'2016-06',:]
mean1 = test.loc[:,test.columns[0]].mean()*12 * 100

mean2 = (test.loc[:,test.columns[0]] - test.loc[:,test.columns[1]]).mean()*12 * 100
std2 = (test.loc[:,test.columns[0]] - test.loc[:,test.columns[1]]).std(ddof =
↪ 1)*np.sqrt(12) * 100

print('Arithmetic mean: {:.2}%'
      '\nArithmetic excess mean: {:.2}%'.format(mean1, mean2))

SterlingDoD = DoD_excess_mean * 11.6 / (np.abs(max_drawdownDoD)/100)
SterlingBench = Benchmark_excess_mean * 11.6 / (np.abs(max_drawdownBench)/100)
BurkeDoD = DoD_excess_mean * 11.6 / (np.sqrt((np.abs(max_drawdownDoD)/100)))
BurkeBench = Benchmark_excess_mean * 11.6 / (np.sqrt((np.abs(max_drawdownBench)/100)))
print('\n\n--Summary of risk measures--'
      '\n---(DoD, FTSE 100)---'
      '\nSharpe ratios: {:.4f}, {:.4f}'
      '\n RAPA: {:.4f}\nTreynor ratios: {:.4f}, {:.4f}\nSortino ratios: {:.4f}, {:.4f}'
      '\nProbability of Shortfall: {:.2f}%, {:.2f}%\nReturn on Prob. of Shortfall:
      ↪ {:.4f}, {:.4f}'
      '\nSterling ratios: {:.4}, {:.4}\nBurke ratios: {:.4}, {:.4}'
      '\nMaximum Drawdown ratios: {:.4}%, {:.4}%'
      '\n-------------------------------------------'
```

```
    .format(sharpeDoD, sharpeBench, RAPA,  TreynorDoD,  TreynorBench,
            SortinoDoD,  SortinoBench,
            100*prob_of_shortfallDoD,  100*prob_of_shortfallBench,
            return_on_probability_shortfallDoD, return_on_probability_shortfallBench,
            SterlingDoD, SterlingBench, BurkeDoD, BurkeBench,
            max_drawdownDoD, max_drawdownBench))


# # Plots

# ## Portfolio values

# In[25]:

plt.clf
plt.cla

df2 = df.loc['2002':'2016',['PPDoD','PPFTSE 100']].copy()
df2.plot(figsize=(10,5))
plt.title('Portfolio values', loc = 'left', fontweight = 'bold')
plt.ylabel('Value')

plt.xlabel('')

ax = plt.gca()
ax.legend(loc=2, fancybox=False, shadow=True, ncol=8)
ax.xaxis.grid(False)
ax.yaxis.grid(alpha = 0.8) # how visible is the lines

ax.axes.get_yaxis().set_major_formatter(
    FuncFormatter(lambda x, p: format(int(x), ',')))
ax.axes.set_facecolor('white')
# plt.figure(figsize=(20,10))

# Saving the figure
savepath = 'C:/Users/Christopher/Dropbox/2. ICMA Centre/PROTEXT
↪ test/ICM_296/Portfolio_values.png'
plt.savefig(savepath,transparent = True, dpi = 300, bbox_inches="tight");


# ## Bar plot for excess return

# In[26]:
```

```python
plt.clf
plt.cla
plt.close('all')

style.use('seaborn-pastel')
# Data to plot
xdata = df.index
ydata0 = df['DoD - FTSE 100 (%)']
# ydata1 = df['PPFTSE 100']

# Setting up the fig3ure environment
fig2 = plt.figure(figsize=(20,10))

# Defining the grid and adding plots
ax2 = plt.subplot2grid((1,1),(0,0), facecolor = 'white')
plt.subplots_adjust(left = 0.05, bottom = 0.1, right = .65, top = 0.95, wspace = 0.0,
 ↪  hspace = 0)

ax2.bar(xdata,ydata0, width=20, label = 'Difference')
# ax1.plot_date(xdata, ydata1, '-', label='FTSE 100')

# Plot title, x-label and y-label
plt.ylabel('Difference')
plt.title('DoD - FTSE 100 (%)', loc = 'left', fontweight="bold")

# Adjusting the tickers on x-axis and y-axis
fig2.autofmt_xdate(rotation=90) # To rotate x-ticks
ax2.xaxis.set_major_locator(mdates.YearLocator())

fmt = '%.0f%%' # Format you want the ticks, e.g. '40%'
yticks = mtick.FormatStrFormatter(fmt)
ax2.yaxis.set_major_formatter(yticks)


# Adjusting the legend box
# box = ax1.get_position()
# ax1.set_position([box.x0, box.y0 + box.height * 0.1,
#     box.width, box.height * 0.9])
# ax1.legend(loc='lower center', bbox_to_anchor=(0.5, 0),
#     fancybox=True, shadow=True, ncol=8)

# Adjusting the grids
```

```
ax2.xaxis.grid(False)
ax2.yaxis.grid(alpha = 1) # how visible is the lines

# plt.tight_layout()

# Saving the fig3ure
savepath = 'C:/Users/Christopher/Dropbox/2. ICMA Centre/PROTEXT
 ↪  test/ICM_296/Excessreturn_bar.png'
plt.savefig(savepath,transparent = True, dpi = 200, bbox_inches="tight");


# ## FTSE 100 Histogram

# In[27]:

plt.clf
plt.cla
plt.close('all')
style.use('bmh')

# Data to plot
y = fama.loc[:,'Rm-Rf']

# n, bins, patches = plt.hist(x, 50, normed=1, facecolor='green', alpha=0.75)
n, bins, patches = plt.hist(y, 20, normed=1, label = 'Distribution', rwidth=.75)
plt.axis([np.min(y)*1.2, np.max(y)*1.3, 0, np.max(n)*1.2])
ax = plt.gca()
ax.set_facecolor('white')
y = mlab.normpdf(bins, np.mean(y), np.std(y, ddof=1))
l = plt.plot(bins, y, 'r--', linewidth=1, label ='Best fit')

# Adjusting the grids
plt.grid(False)
ax.legend(loc = 'upper left')
# plt.tight_layout()
#plt.show() # Might not be necessary to display all the fig3ures

#Etc.
plt.xlabel('Excess return')
plt.title('Histogram of FTSE 100 Excess Return', loc = 'left', fontweight = 'bold')

# Saving the figure
```

```
savepath = 'C:/Users/Christopher/Dropbox/2. ICMA Centre/PROTEXT
↪ test/ICM_296/FTSE100Histogram.png'
plt.savefig(savepath,transparent = True, dpi = 300, bbox_inches="tight");


# ## DoD Histogram

# In[28]:

plt.clf
plt.cla
plt.close('all')

# Data to plot
y = fama.loc[:,'DoD-Rf']

# n, bins, patches = plt.hist(x, 50, normed=1, facecolor='green', alpha=0.75)
n, bins, patches = plt.hist(y, 20, normed=1, label = 'Distribution', rwidth=0.75)
plt.axis([np.min(y)*1.2, np.max(y)*1.3, 0, np.max(n)*1.2])
ax = plt.gca()
ax.set_facecolor('white')
y = mlab.normpdf(bins, np.mean(y), np.std(y, ddof=1))
l = plt.plot(bins, y, 'r--', linewidth=1, label = 'Best fit')

# Adjusting the grids
plt.grid(False)

ax.legend(loc = 'upper left')
# plt.tight_layout()
#Etc.
plt.xlabel('Excess return')
plt.title('Histogram of DoD Excess Return', loc = 'left', fontweight = 'bold')

# Saving the fig3ure
savepath = 'C:/Users/Christopher/Dropbox/2. ICMA Centre/PROTEXT
↪ test/ICM_296/DoDHistogram.png'
plt.savefig(savepath,transparent = True, dpi = 300, bbox_inches="tight");


# ## Rolling STD

# In[29]:
```

```
plt.clf
plt.cla
plt.close('all')
style.use('bmh')

# Data to plot
xdata = fama.index
ydata0 = fama['DoD-Rf'].rolling(3).std()
ydata1 = fama['DoD-Rf'].rolling(6).std()
ydata2 = fama['DoD-Rf'].rolling(12).std()

# Setting up the figure environment
fig5 = plt.figure(figsize=(20,10))

# Defining the grid and adding plots
ax5 = plt.subplot2grid((1,1),(0,0),facecolor='white')
plt.subplots_adjust(left = 0.05, bottom = 0.1, right = .65, top = 0.95, wspace = 0.0,
 ↪  hspace = 0)

ax5.plot_date(xdata, ydata0, '-', label='3-month STD')
ax5.plot_date(xdata, ydata1, '-', label='6-month STD')
ax5.plot_date(xdata, ydata2, '-', label='12-month STD')

plt.plot((np.min(fama.index), np.max(fama.index)), (DoD_excess_std, DoD_excess_std),
 ↪  '--', label ='Constant STD')
plt.plot((np.min(fama.index), np.max(fama.index)),
         (np.sqrt(semi_variance1), np.sqrt(semi_variance1)), '-.', label ='Constant
          ↪  semi-STD')

# Plot title, x-label and y-label
plt.title('Rolling Standard Deviation', loc = 'left', fontweight = 'bold')

# Adjusting the tickers on x-axis and y-axis
fig5.autofmt_xdate(rotation=90)
ax5.xaxis.set_major_locator(mdates.YearLocator())

# Adjusting the legend box

# Adjusting the grids
ax5.xaxis.grid(False)
ax5.yaxis.grid(alpha = 0) # how visible is the lines

ax5.legend(fontsize = 'large')
```

```
ax5.tick_params(axis='x', labelsize=15)
ax5.tick_params(axis='y', labelsize=15)


plt.ylim((0,np.max(ydata0)*1.1))
plt.xlim((xdata.min(), xdata.max()))
# Saving the figure
savepath = 'C:/Users/Christopher/Dropbox/2. ICMA Centre/PROTEXT
↪  test/ICM_296/Rolling_std.png'
plt.savefig(savepath,transparent = True, dpi = 300, bbox_inches="tight");


# ## Rolling std2

# In[30]:

plt.clf
plt.cla
plt.close('all')
style.use('bmh')

# Data to plot
xdata = df.index
ydata0 = (df.loc[:,df.columns[0]]/100).rolling(3).std(ddof = 1)
ydata1 = (df.loc[:,df.columns[1]]/100).rolling(3).std(ddof = 1)

# Setting up the figure environment
fig2 = plt.figure(figsize=(20,10))

# Defining the grid and adding plots
ax2 = plt.subplot2grid((1,1),(0,0),facecolor='white')
plt.subplots_adjust(left = 0.05, bottom = 0.1, right = .65, top = 0.95, wspace = 0.0,
↪  hspace = 0)

ax2.plot_date(xdata, ydata0, '-', label='DoD 3-month Rolling STD')
ax2.plot_date(xdata, ydata1, '-', label='FTSE 100 3-month Rolling STD')

# Plot title, x-label and y-label
# plt.ylabel('Value')
plt.title('Rolling Standard Deviation', loc = 'left', fontweight = 'bold')

# Adjusting the tickers on x-axis and y-axis
fig2.autofmt_xdate(rotation=90)
```

```
ax2.xaxis.set_major_locator(mdates.YearLocator())

# Adjusting the grids
ax2.xaxis.grid(False)
ax2.yaxis.grid(alpha = 0) # how visible is the lines

ax2.legend(fontsize = 'large')
ax2.tick_params(axis='x', labelsize=15)
ax2.tick_params(axis='y', labelsize=15)


plt.ylim((0, np.max(ydata0)*1.1))

# Saving the figure
savepath = 'C:/Users/Christopher/Dropbox/2. ICMA Centre/PROTEXT
↪  test/ICM_296/Rolling_std2.png'
plt.savefig(savepath, transparent = True, dpi = 300, bbox_inches= "tight");


# ## Max Drawdown plot

# In[31]:

plt.clf
plt.cla
plt.close('all')

style.use('fivethirtyeight')

# Data to plot
xdata = df.index
ydata0 = df['PPDoD']

# Setting up the figure environment
fig7 = plt.figure(figsize=(20,10))

# Defining the grid and adding plots
ax7 = plt.subplot2grid((1,1),(0,0),facecolor='white')
plt.subplots_adjust(left = 0.05, bottom = 0.1, right = .65, top = 0.95, wspace = 0.0,
↪  hspace = 0)

ax7.plot_date(xdata, ydata0, '-', label='DoD Portfolio Value')
```

```
plt.plot(('2007-10-31', '2009-02-28'), (df['PPDoD']['2007':'2009'].max(),
↪  df['PPDoD']['2007':'2009'].min()), '-', label = 'Max Drawdown Period')
plt.plot(('2007-10-31', '2009-02-28'), (df['PPDoD']['2007':'2009'].min(),
↪  df['PPDoD']['2007':'2009'].min()), 'r--')
plt.plot(('2007-10-31', '2007-10-31'), (df['PPDoD']['2007':'2009'].max(),
↪  df['PPDoD']['2007':'2009'].min()), 'r--')

# Plot title, x-label and y-label
plt.ylabel('Portfolio Value')
plt.title('Maximum\nDrawdown', loc = 'left', fontweight = 'bold')

# Adjusting the tickers on x-axis and y-axis
fig7.autofmt_xdate(rotation=90)
ax7.xaxis.set_major_locator(mdates.YearLocator())
ax7.axes.get_yaxis().set_major_formatter(
        FuncFormatter(lambda x, p: format(int(x), ',')))

# Adjusting the grids
ax7.xaxis.grid(False)
ax7.yaxis.grid(alpha = 0) # how visible is the lines
ax7.tick_params(axis='x', labelsize=15)
ax7.tick_params(axis='y', labelsize=15)
ax7.legend(loc = 2,fontsize = 'medium')

plt.ylim((0,np.max(ydata0)*1.1))

# Saving the figure
savepath = 'C:/Users/Christopher/Dropbox/2. ICMA Centre/PROTEXT
↪  test/ICM_296/Max_drawdown.png'
plt.savefig(savepath,transparent = True, dpi = 300, bbox_inches="tight");


# In[32]:

end = time.time()

print('-------------------------------------'
      '\n{:.4f} seconds used to load script'
      '\n-------------------------------------'
      .format(end-start));
```

D.2 Part 2

This is the code used to construct the DoD portfolios:

```
# # Preamp

# In[10]:

import numpy as np
import pandas as pd
pd.options.display.float_format = '{:,.2f}'.format

import matplotlib.pyplot as plt
from matplotlib import style
style.use('seaborn-whitegrid')
#print(plt.style.available)
import matplotlib.ticker as mtick
import matplotlib.dates as mdates
import matplotlib.mlab as mlab

import statsmodels.api as sm
from matplotlib.ticker import FuncFormatter
#import pandas_datareader.data as web
#import datetime as dt
import statsmodels.tools

from scipy import stats
import time


# # Importing data

# In[11]:

#import data_to_pickle
start = time.time()

# Read pickles
import read_pickle as pick
import functions as func
# # Organisation of data
```

```
# Here, I organise all the stock prices into the possible investment universes.
# This is done by constructing a dictionary
universe = {}
for i in range(0,len(pick.investmentuniverse.columns)):
    universe [str(i)] =
     ↪  pick.investmentuniverse[pick.investmentuniverse.columns[i]].dropna()
    # Dropna to filter out any missing values


Portfolios = {}
years = []
for i in range (2002, 2016+1):
    years.append(i)
for i in range (2, 17):
    Portfolios [str(i)] = pick.icm[universe[str(i-2)]].loc[str(years[i-2])][1:]

# # Working with dividends
dividends_quarterly = pick.dividends.resample('Q').sum()


# # Portfolios

# ## Portfolio 2002

# In[12]:

test = dividends_quarterly['2001'][Portfolios['2'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪  en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['2'].keys()]['2001'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list2 = summ[1:11]
list2.to_clipboard()
list2 = list2.index
```

```
print(list2)

P02 = pick.totret[list2]['2002']

P02.head()

P02.mean(axis = 1).to_clipboard()
P02.mean(axis = 1)


# ## Portfolio 2003

# In[13]:

test = dividends_quarterly['2002'][Portfolios['3'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪ en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['3'].keys()]['2002'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list3 = summ[1:11]
list3.to_clipboard()
list3 = list3.index

P03 = pick.totret.loc['2003',list3]
P03.head()
P03.mean(axis = 1).to_clipboard()
P03.mean(axis = 1)


# ## Portfolio 2004

# In[14]:

test = dividends_quarterly['2003'][Portfolios['4'].keys()].iloc[2:]
```

```
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪   en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['4'].keys()]['2003'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list4 = summ[1:11]
list4.to_clipboard()
list4 = list4.index

P04 = pick.totret[list4]['2004']
P04.head(2)

P04.mean(1).to_clipboard()
P04.mean(1)


# ## Portfolio 2005

# In[15]:

test = dividends_quarterly['2004'][Portfolios['5'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪   en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['5'].keys()]['2004'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list5 = summ[1:11]
```

```
list5.to_clipboard()
list5 = list5.index

P05 = pick.totret[list5]['2005']

P05.head(2)

P05.mean(1).to_clipboard()
P05.mean(1)


# ## Portfolio 2006

# In[16]:

test = dividends_quarterly['2005'][Portfolios['6'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪  en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['6'].keys()]['2005'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list6 = summ[1:11]
list6.to_clipboard()
list6 = list6.index

P06 = pick.totret[list6]['2006']
P06 ['UKX Index'] = pick.icm['UKX Index']['2006'].resample('m').last().pct_change(1)+1
P06['UKX Index'].iloc[:7] = np.nan

P06.head(8)
P06.mean(1).to_clipboard()
P06.mean(1)


# ## Portfolio 2007
```

```
# In[17]:

test = dividends_quarterly['2006'][Portfolios['7'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪  en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['7'].keys()]['2006'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list7 = summ[:10]
list7.to_clipboard()
list7 = list7.index

P07 = pick.totret[list7]['2007']
P07 ['UKX Index'] = pick.icm['UKX Index']['2007'].resample('m').last().pct_change(1)+1
P07['UKX Index'][:'2007-06-30'] = np.nan # Alliance was acquired by a P/E company

P07.mean(1).to_clipboard()
P07.mean(1)


# ## Portfolio 2008

# In[18]:

test = dividends_quarterly['2007'][Portfolios['8'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪  en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
```

```
summm = summ / pick.icm[Portfolios['8'].keys()]['2007'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list8 = summ[:10]
list8.to_clipboard()
list8 = list8.index

P08 = pick.totret[list8]['2008']
P08 ['UKX Index'] = pick.icm['UKX Index']['2008'].resample('m').last().pct_change(1)+1
P08 ['UKX Index'][:'2008-10-31'] = np.nan # Alliance was acquired by a P/E company

P08.mean(1).to_clipboard()
P08.mean(1)


# ## Portfolio 2009

# In[19]:

test = dividends_quarterly['2008'][Portfolios['9'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
    ↪ en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['9'].keys()]['2008'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list9 = summ[:10]
list9.to_clipboard()
list9 = list9.index

P09 = pick.totret[list9]['2009']
P09.head(4)
P09.mean(1).to_clipboard()
```

```
# ## Portfolio 2010

# In[20]:

test = dividends_quarterly['2009'][Portfolios['10'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪  en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['10'].keys()]['2009'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list10 = summ[:10]
list10.to_clipboard()
list10 = list10.index

P10 = pick.totret[list10]['2010']
P10.mean(1).to_clipboard()


# ## Portfolio 2011

# In[21]:

test = dividends_quarterly['2010'][Portfolios['11'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪  en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['11'].keys()]['2010'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)
```

```
list11 = summ[:10]
list11.to_clipboard()
list11 = list11.index

P11 = pick.totret[list11]['2011']
P11.mean(1).to_clipboard()


# ## Portfolio 2012

# In[22]:

test = dividends_quarterly['2011'][Portfolios['12'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪  en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['12'].keys()]['2011'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list12 = summ[:10]
list12.to_clipboard()
list12 = list12.index

P12 = pick.totret[list12]['2012']
P12.mean(1).to_clipboard()
P12.to_clipboard()


# ## Portfolio 2013

# In[23]:

test = dividends_quarterly['2012'][Portfolios['13'].keys()].iloc[2:]
summ = {}
for col in test:
```

```python
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪ en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['13'].keys()]['2012'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list13 = summ[:10]
list13.to_clipboard()
list13 = list13.index

P13 = pick.totret[list13]['2013']
P13.mean(1).to_clipboard()


# ## Portfolio 2014

# In[24]:

test = dividends_quarterly['2013'][Portfolios['14'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
     ↪ en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['14'].keys()]['2013'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list14 = summ[:10]
list14.to_clipboard()
list14 = list14.index

P14 = pick.totret[list14]['2014']
P14.mean(1).to_clipboard()
```

```
# ## Portfolio 2015

# In[25]:

test = dividends_quarterly['2014'][Portfolios['15'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
    ↪   en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['15'].keys()]['2014'].iloc[-1] * 100
summ = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list15 = summ[:10]
list15.to_clipboard()
list15 = list15.index

P15 = pick.totret[list15]['2015']
P15.mean(1).to_clipboard()


# ## Portfolio 2016

# In[26]:

test = dividends_quarterly['2015'][Portfolios['16'].keys()].iloc[2:]
summ = {}
for col in test:
    valid_col = test.dropna(axis = 1) #Finner alle kolonner som har 2 verdier
    valid_col = valid_col.iloc[-1] #Velger den siste verdien av disse
    summ [str(col)] = test[str(col)].sum() #Legger til alle kolonner med tilhrende sum i
    ↪   en dictionary
    summ = pd.DataFrame(summ, index = [0]) #Lager en ny Dataframe

summ [valid_col.index] = valid_col.values
summ = summ / pick.icm[Portfolios['16'].keys()]['2015'].iloc[-1] * 100
```

```
summm = summ.transpose()
summ = summ.sort_values(summ.columns[0], axis = 0,ascending = False)

list16 = summ[:10]
list16.to_clipboard()
list16 = list16.index

P16 = pick.totret[list16]['2016']
P16.mean(1).to_clipboard()
```