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Innovative Applications of O.R.

Enhancement of equity portfolio performance using data envelopment analysis

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ABSTRACT

This paper examines the applicability of data envelopment analysis (DEA) as a basis of selection criteria for equity portfolios. It is the first DEA application for constructing a combined equity investment strategy that aims to integrate the benefits of both value investing and momentum investing. The 3-quantile portfolios are composed of a comprehensive sample of Finnish non-financial stocks based on their DEA efficiency scores that are calculated using three variants of DEA models (the constant returns-to-scale, the super-efficiency, and the cross-efficiency models). The performance of portfolios is evaluated on the basis of the average return and several risk-adjusted performance metrics throughout the 1994–2010 sample period.

The results show the capability of the DEA approach to add value to equity portfolio selection. The outperformance of the top 3-quantile DEA portfolios in contrast to both the comparable bottom portfolio and the stock market average is statistically significant on the basis of all performance measures employed. The outperformance is slightly more significant when the stock price momentum is included in the DEA variables. The methodology employed offers an interesting alternative for detecting the outperforming stocks of the future by capturing both the price momentum and several dimensions of relative value simultaneously. DEA is particularly useful as a multicriteria methodology in cases in which the number of stocks in the sample is large. It therefore also has useful implications to practical portfolio management.

1. Introduction

Considerable evidence against the efficient stock market hypothesis has been documented over the past three decades. On the one hand, numerous studies have identified the existence of price momentum on stock returns (e.g., see Jegadeesh and Titman, 1993, 2001; Chan et al., 1996, 2000; Rouwenhorst, 1998; Grundy and Martin, 2001; Lewellen, 2002; Korajczyk and Sadka, 2004; Gutierrez and Kelley, 2008; Billio et al., 2011), which refers to the tendency of recent winner stocks to generate abnormal returns also in the near future. On the other hand, there is plenty of international evidence of a value premium (e.g., see Fama and French, 2006; Brown et al., 2008; Barbee et al., 2008), which refers to the tendency of value stocks to outperform glamour stocks for most of the time. Momentum investing has been documented to perform best in the short term (e.g., see Jegadeesh and Titman, 2001; Cooper et al., 2004; Lam et al., 2010), whereas value investing performs better when using longer holding periods (see e.g., Bird and Whitaker, 2003; Rousseau and van Rensburg, 2004; Bird and Casavecchia, 2007a). Since the price of value stocks may remain low for an extended period of time, some scholars have started to examine whether value portfolio selection could be complemented with a timing indicator that shows when to purchase undervalued stocks. Bird and Whitaker (2004) report that the added value attributable to each value and momentum strategy is basically uncorrelated, which enables performance improvement by combining these two strategies. Recently, further evidence of added-value of combining value and momentum strategies has been documented (e.g., see Bird and Casavecchia, 2007a; Bettman et al., 2009; Leivo and Pätäri, 2011). However, the major problem with such a research design is how to combine the value indicator and the momentum indicator into a single selection criterion. In this paper, we test whether data envelopment analysis (DEA) is applicable to resolve this dilemma.

To contribute to the scant literature on DEA applications in the context of equity portfolio selection, this paper examines the efficiency of DEA as a formation criterion for equity portfolios in a case in which input and output factors are derived from indicators of relative valuation of stocks and from the price momentum indicator. Thus applied, the DEA approach can be considered as an alternative for constructing a combined investment strategy that aims to integrate the benefits of both value investing and momentum investing. To our knowledge, this is the first time when the DEA approach is employed for combining value and momentum indicators. As far

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as we know, Pätäri et al. (2010) were the first to document the applicability of DEA in detecting undervalued stocks by capturing several dimensions of relative value simultaneously.[1] However, their research design was limited to the relative value aspect, and did not include any momentum indicators. In addition, only one DEA input parameter (i.e. the stock price) was employed in their study, whereas we also test the efficiency of models that include two input parameters (i.e. the stock price and the enterprise value (henceforth EV)) at the same time. As an additional extension to Pätäri et al. (2010), we also test the added-value of earnings before interests, depreciations, and amortizations (EBITDA) as an output variable. By means of these extensions we can implicitly include the EBITDA/EV ratio in our multicriteria methodology employed for the purpose of portfolio formation. Given that EV also takes into account a company's debt, the inclusion of the EBITDA/EV ratio might solve the problem of spurious undervaluation stemming from the characteristics of the price-related earnings multiples (such as earnings-to-price (henceforth E/P) and cash flow-to-price (henceforth CF/P), for example). As Bird and Casavecchia (2007a) state, a relatively low valuation may be a reflection of parlous financial health, which may not be revealed by price-based valuation multiples. Moreover, Leivo and Pätäri (2011) show that additional dimensions included in EBITDA/EV as a measure of relative value can somewhat enhance the performance of portfolios formed on the basis of composite value measures resting only on price-based multiples.

The structure of the paper is as follows: Section 2 reviews the literature as it relates to value investing, and momentum investing, and their combination. Section 3 describes the data and the methodology employed. The empirical results are discussed in Section 4: the results from the full sample period are introduced first. Based on the ongoing stock market cycle, the full sample period is then divided into bear and bull market periods, and the relative performances of the DEA portfolios are compared to each other and to the stock market average in order to trace the attribution of performance differences. Section 5 concludes with suggestions for future research.

2. Literature review

During the past three decades, a large number of studies have documented the anomalous outperformance of naïve strategies that are based on relative valuation differences between value and glamour stocks.[2] Many later studies have shown not only that the value premium in stock markets is a world-wide phenomenon, but also that the relative efficiency of different valuation criteria varies across both stock markets and the sample period examined. For example, Fama and French (1998) compare the value premiums obtained from using four different portfolio-formation criteria (i.e. B/P, CF/P, E/P and D/P) in 13 major stock markets. According to their results, the classification criterion leading to the greatest value premium varies across countries.[3] Later studies have shown further that the relative efficiency of different valuation criteria also varies across the sample period examined. E.g., according to Dhatt et al. (2004), the most efficient individual valuation multiples in the US stock market during the 1980–1999 period were CF/P and S/P. The authors showed further that using composite value measures expanded the set of efficient portfolios, thereby enabling investors to achieve a wider range of risk-return trade-offs. Leivo and Pätäri (2011) also report the improvement in the risk-adjusted performance of value portfolios in the Finnish stock market when composite value measures were used as portfolio-formation criteria. Thus, the recent empirical evidence is somewhat supportive of the use of multicriteria methodology for the purpose of separating value stocks from glamour stocks.

To our knowledge, the interaction of value and momentum strategies was first discussed by Asness (1997) who concludes that momentum and value are negatively correlated across stocks, yet each is positively related to the cross-section of average stock returns. Parallel to the results of Asness (1997), Bird and Whitaker (2004) report that the best long-only (i.e. no short sales allowed) portfolio performance would be achieved by investing in value-loser stocks if a 6-month price momentum were used as a timing indicator and B/P as a value indicator. According to the authors, value-loser stocks are late in the negative momentum cycle to the extent that they will soon turn around and start generating positive abnormal returns. Instead, Bird and Casavecchia (2007a) report a significant outperformance of value-winner stocks against both the stock market and value-loser stocks when price momentum was used as a sentiment indicator and S/P as a value indicator. The authors also examine the added value of a financial health indicator (Bird and Casavecchia, 2007a) and that of a combined earnings momentum indicator (Bird and Casavecchia, 2007b) as timing indicators, but find their efficiency to be marginal compared to that provided by price momentum indicators.[4] The added value of price momentum to the value investor stems from the fact that value stocks may remain undervalued for an extended period of time, and the momentum indicator could be employed to avoid buying these stocks too early. In this paper, we include the momentum indicator in our DEA variables in order to test its contribution to the profits of the equity investor.

3. Data and methodology

3.1. Sample description

The portfolios employed in testing the applicability of DEA as the basis of stock selection criteria are composed of Finnish nonfinancial stocks quoted on the main list of the Helsinki Stock Exchange (HEX; later OMX Helsinki) during the 1994–2010 period. The Finnish stock market is an interesting subject for this type of analysis in that it suffers from an intermittent "periphery syndrome" caused by the behaviour of international institutional investors who cash their equity positions first from the farthest stock markets during turbulent times. This withdrawal process, coupled with the relatively low liquidity of the Finnish stock market, results in a drop in stock prices that is steeper than simultaneous drops in larger and more liquid stock markets. On the other hand, during bullish times stock prices tend to rise in Finland more than they do in the major stock markets. The 2007–2009 financial crisis provided new evidence of this recurrent phenomenon. As a consequence of the above-mentioned "periphery syndrome", the average volatility of the Finnish stock market has historically been somewhat higher than in the major stock markets. It is therefore likely that pricing errors causing the value

[1] The added value of DEA for the purposes of equity portfolio selection is reported in a few previous papers (e.g., see Powers and McMullen, 2002; Chen, 2008; Kadoya et al., 2008; Dia, 2009; Edirisinghe and Zhang, 2007, 2008, 2010). However, none of them have based their choice of the combination of input and output variables on relative value aspect.

[2] The first scientific evidence of the superior performance of value stocks was provided by Basu (1977), who found that high E/P stocks outperformed low E/P stocks. Among the first to offer parallel evidence of the corresponding value premium for book-to-price (B/P) ratios were Rosenberg et al. (1985), for CF/P ratios Chan et al. (1991) and Lakonishok et al. (1994), for dividend-to-price (D/P) ratios Blume (1980),

[3] According to the results of Fama and French (1998), the B/P criterion resulted in the greatest value premium in six out of 13 regional stock markets (in the USA, the UK, Belgium, Switzerland, Singapore, and Japan) during the 1975–1995 period, whereas the CF/P criterion was the best in 4 stock markets (i.e. in Germany, Italy, Hong Kong, and Australia). The greatest value premium in the Netherlands and Sweden was achieved by dividing stocks into portfolios based on E/P ratios, whereas in France the D/P criterion generated the largest premium.

[4] The results of Chordia and Shivakumar (2006) show that price momentum is actually related to the systematic component of earnings momentum.

premium are also larger in the Finnish market, meaning that the opportunities to earn abnormal profits by means of active investment strategies could also be somewhat better. In fact, recent results from the Finnish stock market reinforce this presumption (e.g., see Leivo and Pätäri, 2011).

In order to avoid survivorship bias, the sample also includes the stocks of the companies that were delisted during the sample period. Adjustments for dividends, splits and capitalization issues are made appropriately. If an issuer has had two or more stock series listed, only the one with a higher liquidity is included in the sample. The stocks of companies with a negative book value and/or whose fiscal year is not a calendar year are excluded. Both the stock market data and the financial statement data are from Datastream, and the latter is supplemented with data collected from financial statements of the companies not included in Datastream. The final sample size ranges from 56 companies (in May 1994) to 126 (in May 2008). The number of companies increases gradually within these dates while decreasing slightly during the last 2 years of the sample period (to 113 in May 2010). The sample includes all Finnish non-financial companies that have been quoted on the main list of the OMX Helsinki and that have met the above-mentioned criteria for inclusion.

3.2. Portfolio-formation methodology

The portfolio-formation criteria employed in this study are based on DEA, which is an efficiency evaluation method based on linear programming, proposed originally by Charnes, Cooper, Rhodes (1978; hereafter CCR). The main advantage of DEA is its ability to combine multiple inputs and outputs of an entity into a single efficiency score without any *a priori* definitions of the relationship between the input and output parameters or their pre-assigned weights. We first calculate efficiency scores for each stock in our sample at an annual frequency on the basis of three DEA models that are the basic CCR model, the super-efficiency model (introduced by Andersen and Petersen, 1993), and the cross-efficiency (henceforth CE) model (introduced by Sexton et al.,1986).[5] Then we divide the stocks into three quantile portfolios based on the ranking of the scores. For the sample employed, the 3-quantile (henceforth quantile for the sake of brevity) portfolios based on the two first-mentioned DEA models turned out to be identical since the number of efficient stocks was always lower than one third of the total sample. As a consequence, all the efficient stocks were positioned in the top-quantile portfolios regardless of which of these two DEA models were used as a portfolio-formation criterion. The results reported for the basic CCR model thus also hold for the super-efficiency model. The weights in the CCR model are restricted only by those stocks that are classified as efficient. The CE model makes it possible to further increase the discriminating power of the DEA, and also to give weight to inefficient stocks in the identification of the best performers (see Anderson et al., 2002, for details). The CE method employed in this paper is analogous to that used by Gregoriou et al. (2005) and is based on the CCR model.[6]

Altogether, we report the results for eight variants of a portfolio-formation criterion. The number of variants stems from the fact that we test four combinations of input and output variables using three variants of DEA models, two of which (i.e. CCR and super-efficiency models) result in identical quantile portfolios. The first combination employs the stock price and enterprise value-per-share (EVPS) as input parameters, and book value-per-share (BPS), dividend-per-share (DPS) and EBITDA-per-share (EBITDAPS) as output parameters and can thus be interpreted to represent a pure composite value (i.e. value-only) criterion without any momentum indicator. The second combination also includes the momentum indicator as the output parameter alongside with the same input and output variables employed in the first variable combination. For validity reasons, the momentum output variable is constructed by multiplying the stock price of the first trading day of May by the stocks' past 6-month return denoted as the investment relative (i.e. one plus return).[7] The third combination differs from the second in that it only includes one input variable (i.e. the stock price). The fourth combination is similar to the third, except that earnings-per-share (EPS) is substituted for EBITDAPS. The choice of input and output variables for the basis of DEA is based on recent results of Leivo and Pätäri (2011) from the same stock market (i.e. the Finnish stock market) as examined in this paper.[8]

DEA efficiency scores are calculated on every rebalancing date that is the first trading day of May, at annual frequency. Variables from the financial statements (i.e. EPS, DPS, BPS, EBITDAPS, and EVPS) are drawn from the latest publications prior to the moment of portfolio reformation.[9] These per-share figures are employed beside stock prices and the price momentum indicator as the basis of DEA. Stock prices are the closing quotes on the formation dates.

3.3. Test procedures for performance comparisons

The performance evaluation of 3-quantile portfolios is based on a time series of their monthly returns. The portfolios are equally weighted every time they are reformed in the beginning of May each year, and then monthly returns are calculated by taking account of changes in the portfolio weights during the 1-year holding period. The intermediate cash flows obtained from delisted stocks within the holding period are reinvested in the remaining stocks of the same portfolio according to prevailing portfolio weights in the beginning of the month following the date of delisting. Taking account of rebalancing implications, continuous stacked time-series of monthly returns for quantile portfolios are generated throughout the 16-year sample period.

The performance of quantile portfolios is evaluated based on the average return, the Sharpe ratio, the skewness- and kurtosis-adjusted Sharpe ratio (henceforth SKASR), and the 2-factor alpha. In order to avoid validity problems stemming from the negative excess returns in the context of the Sharpe ratio comparisons we

[5] For an excellent review of methodological developments in DEA during the three past decades, see Cook and Seiford (2009), and Adler et al. (2002) for a corresponding review of ranking methods in the DEA context. See also Tsou and Huang (2010) for the recent developments in performance ranking methods in the DEA context.

[6] See also Ramón et al. (2010) for the recent discussion on the choice of the weight profiles to be used in the calculation of cross-efficiency scores.

[7] We selected 6-month historical returns as our momentum indicator on the basis of preliminary tests in which we evaluated the performance of pure price momentum strategies based on different length combinations of a selection period and a subsequent holding period for the same sample data as employed in this paper. Recent results from other stock markets also support the use of 6-month past returns as the momentum indicator for the 1-year holding period (e.g. see Figelman, 2007).

[8] Leivo and Pätäri (2011) examine the performance of numerous variations of equity investment strategies. According to the results, investment strategies based on the combination of D/P, EBITDA/EV, B/P multiples and 6-month price momentum performed best in the Finnish stock market during the 1993–2008 sample period that very much overlaps with that employed in this paper. Therefore, it is reasonable to examine the applicability of DEA by forming portfolios based on such combinations of input and output variables that implicitly include the above-mentioned valuation ratios and price momentum indicator. EBITDAPS is replaced with EPS as an output variable in the fourth criteria to find out the performance impact of the earnings measure on the results.

[9] Companies with negative EPS figures are always ranked in the bottom 3-quantile portfolios because the DEA software used in the empirical analysis cannot cope with DEA variables that take positive values for some and negative values for other decision-making units. Recently, Emrouznejad et al. (2010a) suggested a solution for this dilemma, but the proposed semi-oriented radial measure cannot be applied in handling negative EPS figures in this context without the validity problems due to the limitations of the proposed refinement methodology (for details of the boundedness of the methodology, see Emrouznejad et al., 2010b).

use modified versions of Sharpe ratios throughout the study, as follows[10]:

$$SR = \frac{r_i - r_f}{\sigma_i^{(ER/|ER|)}} \tag{1}$$

where r_i = the average monthly return of a portfolio i, r_f = the average monthly risk free rate of the return,[11] σ_i = the standard deviation of the monthly excess returns of a portfolio i, and ER = the average excess return of portfolio i. We use the Sharpe ratio as a representative of total risk-based performance metrics. However, it is often criticized for oversimplifying the concept of risk because all the deviations from the mean, including the positive ones, have a direct impact on the value of the standard deviation. If the return distributions under evaluation are right-skewed the use of standard deviation as a risk surrogate penalizes from the upside potential that is desirable rather than undesirable from the viewpoint of the investor. The use of standard deviation as a measure of investment risk is therefore questioned by many scholars, and many alternative measures aimed at achieving a better match with the investor's true perception of risk are suggested in the financial literature (see e.g., Eling and Schuhmacher, 2007; Pätäri, 2008, 2011, for a comprehensive summary of alternative dispersion measures). For that purpose we employ the SKASR, the risk metrics of which capture the third and the fourth moments of the return distributions being analyzed.[12] Analogously to the approach followed by Favre and Galéano (2002) to determine modified Value-at-Risk, the adjusted Z value (i.e. Z_{CF}) that corresponds to the Z value of normal distribution is calculated first. The so-called Cornish and Fisher (1937) expansion is applied to calculate Z_{CF} as follows:

$$Z_{CF} = Z_C + \frac{1}{6}(Z_C^2 - 1)S + \frac{1}{24}(Z_C^3 - 3Z_C)K - \frac{1}{36}(2Z_C^3 - 5Z_C)S^2 \tag{2}$$

where Z_c is the critical value of the probability based on standard normal distribution, and S denotes Fisher's skewness and K excess kurtosis of the return distribution. Next we calculate the skewness- and kurtosis-adjusted deviation (henceforth SKAD) by multiplying the standard deviation by the ratio Z_{CF}/Z_c. We use the 95% probability level in this paper in determining this ratio. Finally, we substitute SKAD for standard deviation and modify the resulting ratio to capture the validity problem stemming from negative excess returns analogously to Israelsen's (2005) refinement procedure, as follows:

$$SKASR = \frac{r_i - r_f}{SKAD_i^{(ER/|ER|)}} \tag{3}$$

The inclusion of higher moments of return distributions in the performance evaluation of equity portfolios is motivated by the results of Rousseau and van Rensburg (2004), who document significant distributional asymmetries in the return distributions of value and growth portfolios. An additional motivation for controlling for the higher moments of equity portfolio returns is given by Leivo and Pätäri (2011) who report that the inclusion of price momentum in the portfolio-formation criteria increases the asymmetries of return distributions. Their finding is parallel to the results of Harvey and Siddiqque (2000), who show that intermediate-term momentum portfolios are exposed to negative skewness.

In order to find out whether the potential value premium is explained by idiosyncratic risk and/or the firm-size effect, we calculate 2-factor alphas for each quantile portfolio on the basis of a pricing model that includes also the size factor (SMB) besides market return. The size-adjusted alphas for each 3-quantile portfolio are calculated as follows:

$$\alpha_i = r_i - r_f - \beta_{i1}(r_m - r_f) - \beta_{i2}SMB \tag{4}$$

where α_i = the two-factor alpha (the abnormal return over what might be expected based on the two factor model employed), r_i = the return of portfolio i, r_m = the stock market return, r_f = the risk-free rate of return, SMB = the return of size factor (i.e. *small minus big*, which refers to the return difference between small- and large-cap portfolios), and β_{i1}, and β_{i2} are the factor sensitivities to the stock market and SMB factors, respectively. The SMB factor is constructed by classifying the stocks quoted on the main list of OMX Helsinki Stock Exchange into three size portfolios based on the market capitalization of the companies included. The monthly-return time series for the SMB factor are generated by subtracting the value-weighted monthly return of the large-cap 3-quantile portfolio from the comparable return of the small-cap 3-quantile portfolio.[13] If the number of companies at the moment of portfolio formation is not divisible by three the remaining stocks are included in the middle quantile portfolio so that small- and large-cap portfolios always have equal amounts of stocks.[14]

Being aware that there are pricing models that are more sophisticated, we restrict our regression tests to this simple model given that our main interest is in eliminating the impact of the firm-size effect on the portfolio alphas. The motivation for the use of size-adjusted alphas is given, for example, by Loughran (1997) and Phalippou (2008) who report that value premium is, for the most part, driven by small-cap stocks. However, their results are in contrast with Fama and French (2006), who show that the value premium is not restricted to small-cap stocks by rejecting CAPM pricing formed on size, B/P, and market beta during the 1928–2004 period.

3.4. Statistical tests and adjustments

The statistical significances of the differences between comparable pairs of the Sharpe ratios are given by the p-values of the Ledoit–Wolf test,[15] which is based on the circular block bootstrap method. Correspondingly, the significances of the differences between the portfolio alphas are tested by the appropriate t-statistics. Throughout the study we use Newey and West (1987) standard errors in the statistical tests in order to avoid problems related to autocorrelation and heteroscedasticity. In addition, we carried out Jarque and Bera (1980) normality test for regression residuals, but the normality assumption was never violated. We also tested for the existence of multicollinearity in our 2-factor regression model. In spite of the significant negative correlation between the market and SMB factors, the variance inflation factor (VIF), which is typically used to detect degree of multicollinearity (e.g., see Hair et al., 2006), indicates that it is not severe in our tests.

4. Results

4.1. The results from the full sample period

The overall results clearly indicate the capability of DEA methods to separate the best-performing stocks from their worst- and

[10] Israelsen (2005) introduces the modification procedure and also illustrates the validity problems of the Sharpe ratio when comparing performance in conditions of negative excess returns.

[11] The proxy for the risk-free rate is from the Research Institute of the Finnish Economy (ETLA) database from May 1994 until the end of 1998 (1-month Helibor) and from the Datastream database from January 1999 until the end of the sample period (1-month Euribor).

[12] SKASR is introduced by Pätäri (2011).

[13] The SMB factor was first introduced by Fama and French (1993).

[14] The authors would like to thank Professor Mika Vaihekoski for providing us the Finnish SMB factor returns from May 1994 until December 2004. The remaining monthly returns required for the tests from January 2005 till the end of the sample period (i.e., May 2010) were calculated by the authors, respectively.

[15] Because of the complexity of the test procedure and space limitations we do not describe the Ledoit–Wolf test in more detail here, but recommend the interested reader to see the original article (Ledoit and Wolf, 2008; the corresponding programming code is freely available at http://www.econ.uzh.ch/faculty/wolf/publications.html).

Table 1
Performance comparison of 3-quantile DEA portfolios during the full sample period (1994–2010).

Portfolio-formation criterion	3-Quantile portfolio	Average annual return (%)	Annual volatility (%)	SKAD (%)	SR(sign.) Pi vs. market		SKASR (sign.) Pi vs. market		Perf. diff. Pi vs. Pj	SR diff. (sign.)	SKASR diff. (sign.)
CCR1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)											
	P1	16.56	17.16	18.93	0.225	(0.014)	0.205	(0.035)	P1 vs. P3	(0.004)	(0.010)
	P2	10.93	17.92	20.08	0.138	(0.436)	0.124	(0.633)	P1 vs. P2	(0.015)	(0.023)
	P3	8.34	23.55	24.77	0.090	(0.615)	0.086	(0.582)	P2 vs. P3	(0.264)	(0.375)
CCR2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)											
	P1	17.69	17.92	20.15	0.233	(0.004)	0.209	(0.016)	P1 vs. P3	(0.000)	(0.002)
	P2	11.55	18.87	20.78	0.142	(0.316)	0.130	(0.476)	P1 vs. P2	(0.011)	(0.027)
	P3	6.70	21.63	22.34	0.072	(0.380)	0.070	(0.386)	P2 vs. P3	(0.077)	(0.132)
CCR3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)											
	P1	17.65	18.27	20.44	0.229	(0.004)	0.206	(0.016)	P1 vs. P3	(0.001)	(0.002)
	P2	11.68	17.98	20.19	0.149	(0.253)	0.133	(0.437)	P1 vs. P2	(0.021)	(0.036)
	P3	6.57	22.10	22.98	0.070	(0.359)	0.068	(0.360)	P2 vs. P3	(0.050)	(0.102)
CCR4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)											
	P1	16.38	17.74	20.07	0.217	(0.013)	0.193	(0.045)	P1 vs. P3	(0.004)	(0.015)
	P2	11.92	18.73	20.37	0.148	(0.225)	0.137	(0.342)	P1 vs. P2	(0.053)	(0.113)
	P3	7.66	21.81	22.78	0.084	(0.557)	0.080	(0.545)	P2 vs. P3	(0.085)	(0.130)
CE1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)											
	P1	16.33	17.33	19.40	0.220	(0.014)	0.198	(0.043)	P1 vs. P3	(0.006)	(0.020)
	P2	10.75	17.50	19.49	0.137	(0.480)	0.124	(0.656)	P1 vs. P2	(0.017)	(0.032)
	P3	8.30	24.16	24.82	0.089	(0.605)	0.087	(0.613)	P2 vs. P3	(0.318)	(0.443)
CE2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)											
	P1	17.56	18.13	20.36	0.230	(0.004)	0.206	(0.018)	P1 vs. P3	(0.001)	(0.004)
	P2	11.29	18.12	20.30	0.142	(0.343)	0.128	(0.539)	P1 vs. P2	(0.013)	(0.025)
	P3	6.92	22.08	22.56	0.074	(0.402)	0.073	(0.419)	P2 vs. P3	(0.079)	(0.156)
CE3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)											
	P1	17.57	18.49	20.60	0.226	(0.005)	0.204	(0.019)	P1 vs. P3	(0.001)	(0.005)
	P2	11.37	17.79	19.81	0.145	(0.291)	0.131	(0.467)	P1 vs. P2	(0.019)	(0.033)
	P3	6.59	22.03	22.92	0.070	(0.363)	0.068	(0.364)	P2 vs. P3	(0.047)	(0.093)
CE4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)											
	P1	16.29	18.05	20.38	0.213	(0.016)	0.190	(0.053)	P1 vs. P3	(0.007)	(0.023)
	P2	11.79	18.42	20.06	0.148	(0.236)	0.136	(0.357)	P1 vs. P2	(0.077)	(0.146)
	P3	7.57	22.06	22.94	0.082	(0.542)	0.079	(0.536)	P2 vs. P3	(0.086)	(0.135)
Market portfolio		9.84	22.93	23.55	0.108		0.105				

The table presents average annual return, two risk measures (i.e. volatility and SKAD) and corresponding performance metrics (the Sharpe ratio (SR) and SKASR) for every 3-quantile portfolio (P1–P3) formed on the basis of four portfolio formation criteria (1–4 in the first column) and two DEA methods (CCR and CE). P1 refers to the portfolio of stocks that have the highest efficiency scores (i.e. top-quantile portfolio), while P3 refers to the portfolio of stocks that have the lowest efficiency scores (i.e. bottom-quantile portfolios). The numbers following SRs and SKASRs (in parentheses) indicate significance levels for performance differences between each 3-quantile portfolio and market portfolio. The last two columns show significance levels (in parentheses) of performance differences between each pair of quantile portfolios (the reported significances are based on the Ledoit–Wolf test statistics for the Sharpe ratio (SR) difference and the SKASR difference, respectively). The pairs of quantile portfolios being compared in the last two columns are indicated by the third column from the right.

middle-performing counterparts (Table 1). All four combinations of input and output variables employed as portfolio-formation criteria produce parallel results, although some variable combinations lead to more significant performance differences between the quantile portfolios. The most successful variable combination is the second criterion, which includes the largest number of input and output variables in DEA. The average annual return of the corresponding CCR top-quantile portfolio is the highest (i.e. 17.69% p.a.) among all the portfolios being compared, whereas the average stock market return for the same 16-year period is 9.84% p.a. Also the risk-adjusted performance of the same portfolio is the best of all the quantile portfolios on the basis of all three risk-adjusted performance measures employed, and according to the same measures this portfolio also significantly outperforms the stock market portfolio. However, performance differences between the top-quantile portfolios are marginal in most cases. Instead, all the top-quantile portfolios clearly outperform all the middle-quantile portfolios, and all the middle-quantile portfolios outperform all the bottom-quantile portfolios, respectively. Consequently, all the top-quantile portfolios significantly outperform the corresponding bottom-quantile portfolios, and even the outperformance of the top-quantile portfolios against the corresponding middle-quantile portfolios is statistically significant (at the 5% level) for the first three portfolio-formation criteria on the basis of all the performance measures used and regardless of the DEA method employed.

The statistical significance of the outperformance of the middle-quantile portfolio over the corresponding bottom-quantile portfolio is somewhat lower, however. On the basis of the Sharpe ratio difference, the confidence level of 95% in comparisons of these two quantile portfolios is exceeded only for the CE3 formation criterion. The confidence level of 90% in the same comparisons is exceeded for the CCR2, CCR3, CCR4, CE2 and CE4 criteria. Based on the adjusted Sharpe ratio difference, the only significant test statistic (at the 10% level) for performance difference between the middle- and bottom-quantile portfolios is documented for the CE3 criterion. The somewhat lower significances of the SKASR differences compared to those based on the standard Sharpe ratio are explained by differences in the distributional forms of the quantile portfolios. The return distributions are more negatively skewed for the middle-quantile portfolios than for the bottom-quantile portfolios. Nevertheless, all the middle-quantile portfolios dominate the corresponding bottom-quantile portfolios in the mean-variance framework (i.e. the average returns are always higher for the former, whereas their average volatility is always lower than that of the corresponding bottom-quantile portfolios).

The finding that the Sharpe ratios of the DEA quantile portfolios are higher than the corresponding SKASR values for all the portfolio-formation criteria implies that, from an investor's viewpoint, these portfolios are riskier than might be inferred on the basis of volatility when distributional asymmetries of portfolio returns are controlled. The same holds for the market portfolio. Comparisons of the performance differences between the Sharpe ratio and the SKASR reveals that the return distributions of the DEA top-quantile portfolios are slightly more negatively skewed than those of the corresponding bottom-quantile portfolios or that of the market portfolio. This explains the slightly lower significances of performance differences when the latter performance measure is used. In spite of this, the performance differences between the top- and bottom-quantile portfolios, as well as those between the top-quantile portfolios and the market portfolio, remain significant (at the 5% level) also based on the SKASR, except for the CE4 criterion in the latter comparison (However, the corresponding significance level in that case is 5.3% which indicates significance at the 10% level).

On the basis of the market risk-based and size-adjusted performance metrics (i.e. size-adjusted alphas) reported in Table 2, the outperformance of the top-quantile portfolio against the bottom-quantile portfolios is significant at the 1% level in five out of the eight cases, and at the 5% level in the rest. The top-quantile portfolios also outperform the comparable middle-quantile portfolios at the 5% significance level for the first three selection criteria (the corresponding outperformance is also significant at the 10% level for the fourth criterion). However, the 2-factor alpha spread is not statistically significant between the middle- and bottom-quantile portfolios in any of the cases examined, although the annualized alphas are distinctly higher for the former (4.13 percentage points, on average). Thus, the results are in line with those based on total risk-adjusted performance metrics, although small

Table 2
Factor-based performance of 3-quantile DEA portfolios during the full sample period (1994–2010).

Portfolio-formation criterion	3-Quantile portfolio	2-Factor alpha (sign.)		2-Factor market beta	Slope of SMB factor	(sign.)	2-Factor alpha spread (Pi vs. Pj)	2-Factor alpha spread (sign.)		Change in adj. R^2s (%)
CCR1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)										
	P1	8.98%	(0.000)	0.791	0.369	(0.000)	P1 vs. P3	9.10%	(0.005)	20.79
	P2	3.27%	(0.065)	0.822	0.276	(0.000)	P1 vs. P2	5.71%	(0.024)	10.63
	P3	−0.12%	(0.965)	0.994	0.169	(0.002)	P2 vs. P3	3.39%	(0.294)	2.24
CCR2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	9.52%	(0.000)	0.816	0.314	(0.000)	P1 vs. P3	10.52%	(0.002)	13.79
	P2	3.46%	(0.067)	0.869	0.255	(0.000)	P1 vs. P2	6.05%	(0.023)	8.19
	P3	−1.00%	(0.719)	0.927	0.249	(0.000)	P2 vs. P3	4.46%	(0.184)	5.87
CCR3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	9.36%	(0.000)	0.836	0.311	(0.000)	P1 vs. P3	10.52%	(0.004)	13.01
	P2	3.80%	(0.023)	0.833	0.263	(0.000)	P1 vs. P2	5.56%	(0.039)	9.63
	P3	−1.16%	(0.697)	0.940	0.245	(0.000)	P2 vs. P3	4.96%	(0.146)	5.42
CCR4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)										
	P1	8.46%	(0.000)	0.815	0.330	(0.000)	P1 vs. P3	8.55%	(0.012)	15.49
	P2	3.72%	(0.025)	0.860	0.234	(0.000)	P1 vs. P2	4.74%	(0.054)	7.01
	P3	−0.09%	(0.975)	0.934	0.254	(0.000)	P2 vs. P3	3.81%	(0.248)	6.00
CE1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)										
	P1	8.65%	(0.000)	0.802	0.358	(0.000)	P1 vs. P3	8.84%	(0.012)	19.15
	P2	3.38%	(0.052)	0.803	0.306	(0.000)	P1 vs. P2	5.27%	(0.032)	13.68
	P3	−0.19%	(0.951)	1.000	0.150	(0.006)	P2 vs. P3	3.57%	(0.309)	1.63
CE2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	9.37%	(0.000)	0.834	0.326	(0.000)	P1 vs. P3	10.29%	(0.003)	5.87
	P2	3.41%	(0.074)	0.830	0.251	(0.000)	P1 vs. P2	5.96%	(0.022)	14.50
	P3	−0.92%	(0.751)	0.945	0.239	(0.000)	P2 vs. P3	4.33%	(0.211)	8.62
CE3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	9.28%	(0.000)	0.842	0.314	(0.000)	P1 vs. P3	10.41%	(0.005)	12.89
	P2	3.52%	(0.029)	0.825	0.259	(0.000)	P1 vs. P2	5.77%	(0.031)	9.54
	P3	−1.13%	(0.713)	0.938	0.246	(0.000)	P2 vs. P3	4.65%	(0.180)	5.51
CE4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)										
	P1	8.36%	(0.000)	0.829	0.334	(0.000)	P1 vs. P3	8.52%	(0.019)	15.39
	P2	3.68%	(0.050)	0.843	0.233	(0.000)	P1 vs. P2	4.68%	(0.078)	7.14
	P3	−0.17%	(0.957)	0.935	0.248	(0.000)	P2 vs. P3	3.84%	(0.289)	5.56

The table presents annualized size-adjusted (i.e. 2-factor) alphas and regression coefficients of 2-factor models for each 3-quantile portfolio (significances in parentheses). The fourth column indicates the market betas of the 2-factor model followed by the slopes of the size factor in the fifth column. The alpha spreads of quantile portfolios and their significances (in parentheses) are reported in the seventh column, while the pairs of quantile portfolios being compared are indicated by the sixth column. The last column shows the improvement in adjusted coefficients of determination ($R2$s) in percentages when SMB factor is included as another explanatory factor beside stock market excess return in the regression model.

Table 3
Panel A – Performance comparison of 3-quantile DEA portfolios during the bullish periods (1994–2010). Panel B – Factor-based performance of 3-quantile DEA portfolios during the bullish periods (1994–2010).

Portfolio-formation criterion	3-Quantile portfolio	Average annual return (%)	Annual volatility (%)	SKAD (%)	SR (sign.) Pi vs. market	SKASR (sign.) Pi vs. market	Perf. diff. Pi vs. Pj	SR diff. (sign.)	SKASR diff. (sign.)
Panel A									
CR1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)									
	P1	33.12	15.38	14.39	0.502 (0.560)	0.540 (0.339)	P1 vs. P3	(0.058)	(0.269)
	P2	31.00	14.89	14.23	0.485 (0.712)	0.511 (0.109)	P1 vs. P2	(0.748)	(0.582)
	P3	32.26	20.16	16.57	0.386 (0.092)	0.471 (0.008)	P2 vs. P3	(0.098)	(0.512)
CCR2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)									
	P1	36.77	15.75	14.27	0.542 (0.191)	0.601 (0.987)	P1 vs. P3	(0.005)	(0.016)
	P2	31.67	16.23	14.60	0.458 (0.885)	0.512 (0.063)	P1 vs. P2	(0.120)	(0.106)
	P3	27.97	18.38	15.09	0.365 (0.072)	0.446 (0.007)	P2 vs. P3	(0.074)	(0.217)
CCR3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)									
	P1	36.64	16.26	14.55	0.524 (0.289)	0.589 (0.821)	P1 vs. P3	(0.007)	(0.026)
	P2	31.33	15.10	14.30	0.485 (0.695)	0.514 (0.091)	P1 vs. P2	(0.446)	(0.159)
	P3	28.09	18.66	15.01	0.362 (0.057)	0.452 (0.008)	P2 vs. P3	(0.017)	(0.231)
CCR4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)									
	P1	34.45	15.66	14.45	0.512 (0.420)	0.558 (0.470)	P1 vs. P3	(0.036)	(0.190)
	P2	32.51	16.06	14.70	0.475 (0.830)	0.521 (0.089)	P1 vs. P2	(0.480)	(0.488)
	P3	29.37	18.44	14.87	0.381 (0.133)	0.475 (0.029)	P2 vs. P3	(0.064)	(0.369)
CE1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)									
	P1	34.14	15.13	13.92	0.524 (0.346)	0.573 (0.657)	P1 vs. P3	(0.025)	(0.141)
	P2	28.86	14.96	14.47	0.451 (0.811)	0.469 (0.025)	P1 vs. P2	(0.162)	(0.049)
	P3	32.82	20.85	16.69	0.381 (0.090)	0.477 (0.017)	P2 vs. P3	(0.292)	(0.911)
CE2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)									
	P1	36.26	15.92	14.24	0.530 (0.259)	0.595 (0.904)	P1 vs. P3	(0.011)	(0.021)
	P2	30.93	15.50	14.53	0.467 (0.962)	0.501 (0.045)	P1 vs. P2	(0.232)	(0.078)
	P3	28.90	18.86	15.67	0.368 (0.079)	0.445 (0.006)	P2 vs. P3	(0.058)	(0.292)
CE3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)									
	P1	36.78	16.32	14.21	0.525 (0.293)	0.606 (0.953)	P1 vs. P3	(0.011)	(0.016)
	P2	30.98	15.13	14.37	0.479 (0.781)	0.506 (0.060)	P1 vs. P2	(0.375)	(0.061)
	P3	27.97	18.65	15.13	0.360 (0.057)	0.446 (0.007)	P2 vs. P3	(0.016)	(0.226)
CE4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)									
	P1	35.45	15.85	14.07	0.520 (0.351)	0.589 (0.834)	P1 vs. P3	(0.031)	(0.079)
	P2	31.17	15.91	14.92	0.460 (0.914)	0.493 (0.021)	P1 vs. P2	(0.282)	(0.093)
	P3	29.46	18.63	15.05	0.379 (0.128)	0.471 (0.027)	P2 vs. P3	(0.101)	(0.667)
Market portfolio		36.86	18.71	14.50	0.465	0.602			

Portfolio-formation criterion	3-Quantile portfolio	2-Factor alpha (sign.)		2-Factor market beta	Slope of SMB factor	(sign.)	2-Factor alpha spread (Pi vs. Pj)	2-Factor alpha spread (sign.)		Change in adj. $R2$s (%)
Panel B										
CCR1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)										
	P1	8.55%	(0.000)	0.807	0.363	(0.000)	P1 vs. P3	9.41%	(0.013)	21.56
	P2	5.89%	(0.020)	0.791	0.276	(0.000)	P1 vs. P2	2.66%	(0.429)	13.30
	P3	−0.87%	(0.776)	1.010	0.160	(0.007)	P2 vs. P3	6.75%	(0.087)	2.32
CCR2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	9.88%	(0.000)	0.819	0.295	(0.000)	P1 vs. P3	10.13%	(0.006)	13.58
	P2	3.39%	(0.148)	0.871	0.229	(0.000)	P1 vs. P2	6.49%	(0.037)	7.67
	P3	−0.24%	(0.936)	0.931	0.274	(0.000)	P2 vs. P3	3.64%	(0.342)	8.51
CCR3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	8.67%	(0.000)	0.855	0.291	(0.000)	P1 vs. P3	9.43%	(0.014)	12.35
	P2	5.10%	(0.019)	0.807	0.242	(0.000)	P1 vs. P2	3.57%	(0.253)	9.90
	P3	−0.76%	(0.806)	0.949	0.268	(0.000)	P2 vs. P3	5.86%	(0.119)	7.89
CCR4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)										
	P1	8.24%	(0.000)	0.824	0.313	(0.000)	P1 vs. P3	7.41%	(0.058)	15.42
	P2	4.16%	(0.052)	0.857	0.212	(0.000)	P1 vs. P2	4.08%	(0.177)	6.73
	P3	0.83%	(0.799)	0.931	0.272	(0.000)	P2 vs. P3	3.33%	(0.392)	8.34
CE1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)										
	P1	9.41%	(0.000)	0.794	0.347	(0.000)	P1 vs. P3	10.11%	(0.014)	20.33
	P2	4.60%	(0.039)	0.791	0.300	(0.000)	P1 vs. P2	4.81%	(0.126)	15.58
	P3	−0.70%	(0.839)	1.019	0.153	(0.016)	P2 vs. P3	5.31%	(0.196)	1.92

(*continued on next page*)

Table 3 (*continued*)

Portfolio-formation criterion	3-Quantile portfolio	2-Factor alpha (sign.)	2-Factor market beta	Slope of SMB factor	(sign.)	2-Factor alpha spread (Pi vs. Pj)	2-Factor alpha spread (sign.)	Change in adj. $R2$s (%)
CE2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)								
	P1	9.09% (0.000)	0.842	0.312	(0.000)	P1 vs. P3	9.26% (0.021)	14.88
	P2	4.04% (0.089)	0.825	0.225	(0.000)	P1 vs. P2	5.04% (0.097)	8.13
	P3	−0.18% (0.960)	0.946	0.257	(0.000)	P2 vs. P3	4.22% (0.320)	7.09
CE3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)								
	P1	8.83% (0.000)	0.853	0.289	(0.000)	P1 vs. P3	9.51% (0.015)	12.12
	P2	4.64% (0.036)	0.813	0.240	(0.000)	P1 vs. P2	4.19% (0.176)	9.74
	P3	−0.68% (0.833)	0.945	0.270	(0.000)	P2 vs. P3	5.32% (0.173)	8.04
CE4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)								
	P1	8.93% (0.000)	0.830	0.319	(0.000)	P1 vs. P3	8.10% (0.041)	15.64
	P2	3.29% (0.182)	0.847	0.205	(0.000)	P1 vs. P2	5.64% (0.075)	6.40
	P3	0.84% (0.806)	0.933	0.269	(0.000)	P2 vs. P3	2.45% (0.558)	7.99

Panel A presents average annual return, two risk measures (i.e. volatility and SKAD) and corresponding performance metrics (the Sharpe ratio (SR) and SKASR) for every 3-quantile portfolio (P1–P3) formed on the basis of four portfolio formation criteria (1–4 in the first column) and two DEA methods (CCR and CE). P1 refers to the portfolio of stocks that have the highest efficiency scores (i.e. top-quantile portfolio), while P3 refers to the portfolio of stocks that have the lowest efficiency scores (i.e. bottom-quantile portfolios). The numbers following SRs and SKASRs (in parentheses) indicate significance levels for performance differences between each 3-quantile portfolio and market portfolio. The last two columns show significance levels (in parentheses) of performance differences between each pair of quantile portfolios (the reported significances are based on the Ledoit–Wolf test statistics for the Sharpe ratio (SR) difference and the SKASR difference, respectively). The pairs of quantile portfolios being compared in the last two columns are indicated by the third column from the right. The aggregate bull market period includes 145 months and consists of five distinct bullish periods.
Panel B presents annualized size-adjusted (i.e. 2-factor) alphas and regression coefficients of 2-factor models for each 3-quantile portfolio (significances in parentheses). The fourth column indicates the market betas of the 2-factor model followed by the slopes of the size factor in the fifth column. The alpha spreads of quantile portfolios and their significances (in parentheses) are reported in the seventh column, while the pairs of quantile portfolios being compared are indicated by the sixth column. The last column shows the improvement in adjusted coefficients of determination ($R2$s) in percentages when SMB factor is included as another explanatory factor beside stock market excess return in the regression model.

differences in the degree of statistical significance between the performance evaluation methods exist.

Table 2 also indicates that SMB factor is a highly significant explanatory variable for every quantile portfolio, although the top-quantile portfolios are more sensitive to it than the bottom-quantile portfolios. In contrast, the stock market betas are somewhat higher for the bottom-quantile portfolios than for the top-quantile portfolios. In this sense, our results are parallel to Fama and French (2006) who report lower stock market betas for value stocks than for glamour stocks during the 1963–2004 period.

On the basis of the comparison between the first and second criteria, adding momentum variable into the DEA model does not dramatically affect the results. In this particular case it somewhat increases both the average return and the volatility, resulting only in minor changes in risk-adjusted performance.[16] While both versions of the Sharpe ratios remain practically the same, the inclusion of momentum output variable increases the average annual size-adjusted alpha of top-quantile portfolios by 0.63 percentage points. However, the inclusion of momentum somewhat reinforces the significance levels of performance differences between the top-quantile portfolios and the market portfolio. The same also holds for the comparison of the top- and bottom-quantile portfolios. It is also noteworthy that regardless of the performance metrics employed, the inclusion of momentum seems to increase the performance difference between the top- and bottom-quantile portfolios by deteriorating the performance of the latter.

[16] However, this does not imply that quantile portfolios with and without the momentum criterion are identical. To check this we calculate the proportions of stocks that are the same in portfolios formed on the basis of both the first (i.e. value-only criterion) and the second (i.e. combined value-momentum) criterion. The proportions are 77.7%, 68.6% and 83.7% for the top-, middle- and bottom-quantile portfolios, respectively, when the quantile division is based on the CCR model, and 74.0%, 64.7%, and 83.3%, respectively, based on the CE model.

4.2. Decomposition of portfolio performance based on bull and bear market periods

The previous results from the full sample period show that investing in DEA top-quantile portfolios would really have paid off in the Finnish stock market during the 1994–2010 period. In order to trace to what the outperformance of such portfolios was attributable, we perform an additional test by dividing the sample period into bear and bull market conditions according to the overall development of the Finnish stock market. In order to separate bullish and bearish periods we use a simple filter rule according to which a 25% gain (loss) in the value of the market portfolio from the previous tough (peak) is required to determine the ongoing period as bullish (bearish). As a result, we get an aggregate bull market period that includes 145 monthly returns and consists of five distinct bullish periods (i.e. May 94–July 98, October 98–April 00, October 01–March 02, April 03–October 07, and March 09–April 10). The aggregate bear market period is constructed from the remaining months of the full sample period from May 1994 to April 2010 including four distinct bearish periods (47 months in total).

Decomposition of portfolio performance based on bull and bear market periods reveals that, regardless of the small performance differences between the top-quantile portfolios, their performance in relation to other quantile portfolios varies more during the separate bearish and bullish periods (Tables 3 and 4) than during the full sample period. For example, the average return difference between the value-only portfolios and the glamour-only portfolios (i.e. those based on the first criterion) during the bullish periods is marginal (i.e. 1.09% p.a.), although the former are distinctly less volatile than the latter (by 5.25 percentage points). Instead, the corresponding return differences when the momentum indicator is also included in the DEA variables are bigger (i.e. 7.43%, on average), whereas the corresponding volatility differences are smaller

Table 4
Panel A – Performance comparison of 3-quantile DEA portfolios during the bearish periods (1994–2010). Panel B – Factor-based performance of 3-quantile DEA portfolios during the bearish periods (1994–2010).

Portfolio-formation criterion	3-Quantile portfolio	Average annual return (%)	Annual volatility (%)	SKAD (%)	SR $\times 10^{-3}$ (sign.) Pi vs. market		SKASR $\times 10^{-3}$ (sign.) Pi vs. market		Perf. diff. Pi vs. Pj	SR diff. (sign.)	SKASR diff. (sign.)
Panel A											
CCR1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)											
	P1	−22.63	17.03	20.05	−1.15	(0.000)	−1.35	(0.000)	P1 vs. P3	(0.000)	(0.000)
	P2	−33.60	18.62	20.06	−1.91	(0.000)	−2.05	(0.010)	P1 vs. P2	(0.000)	(0.005)
	P3	−41.45	24.84	25.63	−3.18	(0.648)	−3.28	(0.694)	P2 vs. P3	(0.005)	(0.012)
CCR2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)											
	P1	−25.97	17.67	20.97	−1.37	(0.000)	−1.62	(0.001)	P1 vs. P3	(0.000)	(0.011)
	P2	−33.11	19.01	21.43	−1.91	(0.000)	−2.15	(0.017)	P1 vs. P2	(0.008)	(0.038)
	P3	−39.09	23.22	22.73	−2.79	(0.240)	−2.73	(0.459)	P2 vs. P3	(0.044)	(0.198)
CCR3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)											
	P1	−25.85	17.77	21.27	−1.37	(0.000)	−1.64	(0.001)	P1 vs. P3	(0.001)	(0.014)
	P2	−32.25	18.72	20.84	−1.83	(0.000)	−2.03	(0.006)	P1 vs. P2	(0.018)	(0.092)
	P3	−39.59	24.20	23.80	−2.94	(0.400)	−2.89	(0.696)	P2 vs. P3	(0.019)	(0.081)
CCR4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)											
	P1	−25.46	17.70	20.88	−1.34	(0.000)	−1.58	(0.001)	P1 vs. P3	(0.001)	(0.012)
	P2	−33.52	18.62	20.63	−1.90	(0.000)	−2.11	(0.007)	P1 vs. P2	(0.004)	(0.027)
	P3	−38.92	23.61	23.56	−2.82	(0.269)	−2.81	(0.567)	P2 vs. P3	(0.022)	(0.094)
CE1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)											
	P1	−25.03	17.64	20.62	−1.31	(0.000)	−1.53	(0.001)	P1 vs. P3	(0.000)	(0.001)
	P2	−30.60	18.07	19.94	−1.67	(0.000)	−1.84	(0.004)	P1 vs. P2	(0.042)	(0.135)
	P3	−42.29	25.07	25.39	−3.29	(0.808)	−3.33	(0.599)	P2 vs. P3	(0.001)	(0.005)
CE2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)											
	P1	−25.44	18.35	21.60	−1.38	(0.000)	−1.63	(0.001)	P1 vs. P3	(0.001)	(0.011)
	P2	−32.60	18.18	20.90	−1.80	(0.000)	−2.07	(0.014)	P1 vs. P2	(0.025)	(0.066)
	P3	−39.94	23.36	22.47	−2.88	(0.301)	−2.77	(0.507)	P2 vs. P3	(0.007)	(0.082)
CE3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)											
	P1	−26.31	18.41	21.61	−1.44	(0.000)	−1.69	(0.002)	P1 vs. P3	(0.003)	(0.025)
	P2	−32.47	17.82	20.13	−1.76	(0.000)	−1.99	(0.004)	P1 vs. P2	(0.058)	(0.148)
	P3	−39.35	24.06	23.79	−2.90	(0.353)	−2.87	(0.661)	P2 vs. P3	(0.007)	(0.047)
CE4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)											
	P1	−27.34	17.77	21.31	−1.45	(0.000)	−1.74	(0.004)	P1 vs. P3	(0.003)	(0.035)
	P2	−31.73	18.54	20.33	−1.78	(0.000)	−1.95	(0.002)	P1 vs. P2	(0.072)	(0.302)
	P3	−39.27	24.01	23.68	−2.89	(0.345)	−2.85	(0.635)	P2 vs. P3	(0.010)	(0.043)
Market portfolio		−44.28	24.20	21.64	−3.39		−3.03				

Portfolio-formation criterion	3-Quantile portfolio	2-Factor alpha (sign.)		2-Factor market beta	Slope of SMB factor	(sign.)	2-Factor alpha spread (Pi vs. Pj)	2-Factor alpha spread (sign.)		Change in adj. $R2$s (%)
Panel B										
CCR1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)										
	P1	6.22%	(0.116)	0.755	0.376	(0.000)	P1 vs. P3	7.76%	(0.363)	31.29
	P2	−2.25%	(0.557)	0.814	0.274	(0.000)	P1 vs. P2	8.47%	(0.122)	13.60
	P3	−1.54%	(0.839)	0.970	0.182	(0.093)	P2 vs. P3	−0.71%	(0.933)	2.86
CCR2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	4.61%	(0.207)	0.784	0.343	(0.000)	P1 vs. P3	7.63%	(0.388)	24.01
	P2	0.34%	(0.922)	0.856	0.298	(0.000)	P1 vs. P2	4.27%	(0.399)	15.73
	P3	−3.02%	(0.708)	0.895	0.201	(0.093)	P2 vs. P3	3.36%	(0.702)	4.10
CCR3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	5.19%	(0.235)	0.790	0.341	(0.000)	P1 vs. P3	8.14%	(0.435)	23.57
	P2	1.11%	(0.761)	0.851	0.303	(0.000)	P1 vs. P2	4.09%	(0.470)	16.76
	P3	−2.94%	(0.756)	0.905	0.200	(0.124)	P2 vs. P3	4.05%	(0.689)	3.60
CCR4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)										
	P1	5.00%	(0.183)	0.785	0.355	(0.000)	P1 vs. P3	7.10%	(0.436)	25.75
	P2	−0.53%	(0.850)	0.840	0.270	(0.000)	P1 vs. P2	5.53%	(0.235)	13.36
	P3	−2.10%	(0.801)	0.912	0.218	(0.070)	P2 vs. P3	1.57%	(0.858)	4.79
CE1 (inputs: stock price and EVPS – outputs: BPS, DPS and EBITDAPS)										
	P1	5.34%	(0.149)	0.790	0.375	(0.000)	P1 vs. P3	7.77%	(0.391)	29.09
	P2	−0.59%	(0.894)	0.788	0.313	(0.000)	P1 vs. P2	5.93%	(0.300)	19.01
	P3	−2.43%	(0.769)	0.958	0.140	(0.180)	P2 vs. P3	1.84%	(0.844)	1.38
CE2 (inputs: stock price and EVPS – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	7.03%	(0.066)	0.814	0.347	(0.000)	P1 vs. P3	10.11%	(0.266)	22.86
	P2	−1.86%	(0.610)	0.806	0.294	(0.000)	P1 vs. P2	8.89%	(0.091)	16.56
	P3	−3.08%	(0.709)	0.917	0.203	(0.073)	P2 vs. P3	1.23%	(0.891)	4.24

(*continued on next page*)

Table 4 (*continued*)

Portfolio-formation criterion	3-Quantile portfolio	2-Factor alpha (sign.)		2-Factor market beta	Slope of SMB factor	(sign.)	2-Factor alpha spread (Pi vs. Pj)	2-Factor alpha spread (sign.)		Change in adj. *R2*s (%)
CE3 (input: stock price – outputs: BPS, DPS, EBITDAPS and price momentum indicator)										
	P1	5.85%	(0.161)	0.815	0.353	(0.000)	P1 vs. P3	8.16%	(0.421)	23.40
	P2	−1.46%	(0.566)	0.809	0.290	(0.000)	P1 vs. P2	7.31%	(0.134)	16.94
	P3	−2.31%	(0.803)	0.910	0.199	(0.116)	P2 vs. P3	0.85%	(0.930)	3.67
CE4 (input: stock price – outputs: BPS, DPS, EPS and price momentum indicator)										
	P1	2.84%	(0.482)	0.790	0.356	(0.000)	P1 vs. P3	5.29%	(0.599)	25.68
	P2	1.54%	(0.682)	0.836	0.279	(0.000)	P1 vs. P2	1.30%	(0.813)	14.46
	P3	−2.45%	(0.791)	0.908	0.206	(0.099)	P2 vs. P3	3.99%	(0.689)	3.96

Panel A presents average annual return, two risk measures (i.e. volatility and SKAD) and corresponding performance metrics (the Sharpe ratio (SR) and SKASR) for every 3-quantile portfolio (P1–P3) formed on the basis of four portfolio formation criteria (1–4 in the first column) and two DEA methods (CCR and CE). P1 refers to the portfolio of stocks that have the highest efficiency scores (i.e. top-quantile portfolio), while P3 refers to the portfolio of stocks that have the lowest efficiency scores (i.e. bottom-quantile portfolios). The numbers following SRs and SKASRs (in parentheses) indicate significance levels for performance differences between each 3-quantile portfolio and market portfolio. The last two columns show significance levels (in parentheses) of performance differences between each pair of quantile portfolios (the reported significances are based on the Ledoit–Wolf test statistics for the Sharpe ratio (SR) difference and the SKASR difference, respectively). The pairs of quantile portfolios being compared in the last two columns are indicated by the third column from the right. The aggregate bear market period includes 47 months and consists of four distinct bearish periods.
Panel B presents annualized size-adjusted (i.e. 2-factor) alphas and regression coefficients of 2-factor models for each 3-quantile portfolio (significances in parentheses). The fourth column indicates the market betas of the 2-factor model followed by the slopes of the size factor in the fifth column. The alpha spreads of quantile portfolios and their significances (in parentheses) are reported in the seventh column, while the pairs of quantile portfolios being compared are indicated by the sixth column. The last column shows the improvement in adjusted coefficients of determination (*R2*s) in percentages when SMB factor is included as another explanatory factor beside stock market excess return in the regression model.

(i.e. 2.65%, on average). Moreover, on the basis of both the standard Sharpe ratio (Table 3, Panel A) and the size-adjusted alphas (Table 3, Panel B), the outperformance of all the top-quantile portfolios over the comparable bottom-quantile portfolios is also significant (at the 10% level) during the bullish periods. Instead, when skewness and kurtosis are taken into account in performance comparisons the statistical significance disappears in some cases. As a result, the performance differences between value-only and glamour-only portfolios (i.e. based on CCR1 and CE1 criteria) are not significant during bullish conditions based on the SKASR. The same holds also for the CCR4 criterion.

In contrast to the bull-period results, the average return differences between the top- and bottom-quantile portfolios during bearish periods are higher for the first criterion that do not take account of the momentum than for the other three criteria, all of which include the momentum criterion (For the former criteria it is 18.04% p.a. while for the latter, it is 13.30%. See Table 4, Panel A). In this respect, our findings are consistent with recent evidence from the major stock markets, according to which momentum profits are dependent on market states. Cooper et al. (2004), for example, show that investors' overconfidence is more accentuated after market gains. Consequently, momentum profits are positive only after stock market increases. Moreover, Avramov and Chordia (2006) and Antoniou et al. (2007) prove that momentum profits are largely attributable to asset mispricing, which systematically varies with the business cycle.

The performance differences between the top-quantile portfolios and the corresponding bottom-quantile portfolios are significant during bearish conditions on the basis of both the standard Sharpe ratio and the SKASR. However, the corresponding 2-factor alpha spread is not significant in any of the cases examined due to the high standard errors in the bear-period alphas, in spite of the fact that the alpha spreads between the top- and bottom-quantile portfolios are relatively high in percentage terms (Table 4, Panel B). The analysis of regression coefficients reveals that the SMB factor significantly explains the variability in returns of the top-quantile portfolios during bearish periods, whereas the significance is not so evident for the bottom-quantile portfolios.[17] In contrast, the SMB is significant for every quantile portfolio in bullish periods (Table 3, Panel B). In such conditions, the SMB betas of the top- and bottom-quantile portfolios are very close to each other for all the other portfolio-formation criteria except the first. Although the SMB is mostly significant in terms of explaining the returns of all quantile portfolios, their exposure to it seems to vary according to general stock market conditions.

It is also noteworthy that all the DEA top-quantile portfolios dominate the corresponding bottom-quantile portfolios during both bearish and bullish periods, both in the mean-variance framework and in the mean-SKAD framework. Interestingly, the top-quantile DEA portfolios lose far less of their values during bearish periods than the comparable bottom-quantile portfolios. In this sense, our results are parallel to those of Pätäri et al. (2010). The same phenomenon, though based on different portfolio-formation criteria that include only relative value aspect, is also documented by Lakonishok et al. (1994) and Bird and Whitaker (2003). The recent findings of Gulen et al. (2011) on the time-variability of the value premium are also consistent with our results.[18] Our general results are also parallel to the previous studies which have shown the applicability of DEA methods for the purposes of equity portfolio selection (e.g., see Kadoya et al., 2008; Dia, 2009; Edirisinghe and Zhang, 2007, 2008, 2010). However, it should be noted that the last-mentioned papers have employed different types of input and output variables, and therefore their results are not directly comparable to ours. Our results are neither directly comparable with those of Pätäri et al. (2010) since their reported results are based on scale-efficiency DEA scores and on a smaller number of input and output variables.

5. Conclusions

This paper examines the applicability of DEA as a basis for stock selection criteria. To our best knowledge, this is the first time when the DEA approach is employed for combining value and momentum indicators into a single efficiency score. Using the Finnish sample data over the 1994–2010 period 3-quantile portfolios of non-financial stocks are formed on the basis of their DEA efficiency scores. The performance of each portfolio is evaluated on the basis of stacked

[17] SMB is insignificant in explaining the variability of bottom-quantile portfolio returns at the 5% level, but at the 10% level it is significant for the CCR1, CCR2, CCR4, CE2 and CE4 criterion.

[18] Gulen et al. (2011) find that the value premium based on B/P ratios is countercyclical.

time-series of monthly returns throughout the 16-year period. The results show that the DEA efficiency scores provide a useful basis for equity portfolio selection. The DEA top-quantile portfolios (i.e. value-only/value-winner portfolios) significantly outperform both the comparable bottom-quantile (i.e. glamour-only/glamour-loser) portfolios and the market portfolio based on all the performance metrics employed. The outperformance improves slightly when stock price momentum is included in the DEA variables.

Based on the results, DEA seems to provide a highly selective approach to portfolio formation, since most of the criteria employed are capable of classifying stocks in such a way that not only do the top-quantile portfolios outperform both the market portfolio and the corresponding bottom-quantile portfolios, but also the middle-quantile portfolios outperform the comparable bottom-quantile portfolios. To our knowledge, such strong performance differences have not been reported in earlier peer-reviewed studies that have employed the comparable 3-quantile approach of dividing stocks into portfolios. Consistently with the previous literature, the division of the full sample period into bullish and bearish periods reveals that the top-quantile DEA portfolios lose far less of their value during the bearish conditions than do the corresponding bottom portfolios.

This paper suggests several potential extensions for further research; our results show that basing the portfolio formation-criterion on different DEA methods has only a marginal impact on performance of comparable 3-quantile portfolios. In the light of this finding, it would be interesting in forthcoming studies to examine whether the weighting system employed in DEA would change the contents and the relative performance of quantile portfolios in comparison to counterpart portfolios formed on the basis of other multicriteria methodologies (e.g., see Ben Abdelaziz et al. (2007) for the introduction of such a methodology). Furthermore, the size of the sample in our study is not large in spite of its comprehensiveness from the local stock market aspect. Thus, the DEA methods employed in this paper could be applied to other larger stock markets to examine to what extent our results are generalizable. Furthermore, several combinations and permutations of input and output variables could be tested to find the set of variables that leads to the best performance in each stock market.

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