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INVESTMENT STYLE PREFERENCE AND ITS EFFECT UPON PERFORMANCE OF TRACKING PORTFOLIOS

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Abstract

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Any task of portfolio creation requires that a suitable pre-selection of assets is made, out of which the resultant portfolio is to be formed. Several approaches in passive investing implemented through portfolio tracking are applied in practice, and assets are pre-selected frequently on the basis of their capitalization or value/growth potential. The paper studies to which extent the investment style practiced by a small investor affects the performance of the tracking portfolio. The design of the analysis is experimental and hinges on tracking the S & P 500 Index in three different periods with assets pre-selected by diverse investment styles. Taking the approach of with linear and quadratic tracking, two factors are analyzed on that occasion: the investment style (big vs. small market capitalization, value vs. growth assets, Fama-French stratas of assets) and the number of assets (10, 20, 30, 40, 50 assets). It is found that while small market capitalization portfolios were preferable in the first two parts of the investigated time frame, this pattern ceased to hold in the third last part with no guidance for a recommendable investment style.

Keywords: investment style, market capitalization, value/growth, Fama-French classification, performance, linear tracking, quadratic tracking, transaction costs

INTRODUCTION

The paper focuses on a small investor who desires to create a tracking portfolio that would be capable of copying or improving the performance of a suitable chosen market index. There are at least two inevitable problems that such an investor must address, and these are (i) how to qualify assets for the resulting tracking portfolio, and (ii) how to determine their shares. For a small investor, it is obviously not viable to take a full replication approach, but he must choose a smaller sample of assets and then specify their weights under some criterion. The first choice should be made in compliance with his investment style, whereas the second choice is associated with a particular model of portfolio tracking. With the intention to sketch some practical advice for investors, in the first regard the paper considers several investment styles and compares their usefulness in an experimental design aiming at tracking the S & P 500 Index, and in the second regard the paper considers the conventional model of both linear tracking and quadratic tracking.

Several academic studies have suggested the existence of categories of stocks with similar characteristics and performance patterns, which is then reflected in differentiated performance in the dimensions "return – risk" amongst these categories. The first such study is Farrell (1975) who calls these categories of stocks clusters, and identifies no less then four clusters for stocks: growth, cyclical, stable and energy. Since then, several classification systems have been developed. For instance, Fabozzi (1998, 2002) promotes classification into value and growth stocks grounded in the P/B ratio. Chan *et al.* (2002) emphasize an exploratory investigation of investment styles as a compromise between stock market capitalization and book-to-market ratio, although they simultaneously control for past stock returns. These authors apply two style identification procedures, i.e. a procedure based on properties of portfolio holdings and a procedure based on estimated loadings from factor models. Absolute past performance is highlighted by De Long *et al.* (1990), Hong and Stein (1999), Barberis and Schleifer (2003). Another approach is to make use of the methodology published by Morningstar Corporation as chosen by Schadler and Eakins (2001) who divide stocks into a 3×3 matrix whose cells arise by combining market capitalization (large, medium, smal) and information embedded in the P/E and P/E ratios (growth, mixed, value). To narrow down the sample of stock within each category they recommend further ordering based on values of the P/S ratio. Eventually, usefulness of this particular multiple is also stressed by Barbee *et al.* (1996) and Gold and Lebowitz (1999).

An investment style is a preference for a particular category of assets that an investor picks in accordance with his risk profile and belief that an investment in the assets falling into this category will ensure him satisfactory return relative to the risk he is willing to take. This vague definition (and everyone is free to come up with any definition of the like) means that the investor reduces the universe of assets to a feasible sample that will qualify for his investment. An example of such a sample in the case of equity investing is "large cap" or "value" stocks, in which either the criterion of market capitalization or an adequate financial metric is chosen. Recognizing several investment styles and resorting to the task of tracking the S & P 500 Index, the paper classifies the S & P 500 Index constituents according to market capitalization into large/big cap stocks ("B") and small cap stocks ("S"), according to their underpricing status into value stocks ("V") and growth stocks ("G"), and according to the definition introduced by Fama and French (1993) into "BH", "BM", "BL", "SH", "SM" and "SL" stocks. Each asset category permits sensible ordering of stocks, which is then the basis for selecting 10, 20, 30, 40 or 50 stocks from amongst the S & P 500 Index constituents for a small portfolio whose actual composition is chosen by running a program of linear or quadratic optimization. Using a weekly frequency and three time samples of historical data spanning across the period from 2011 to 2015, the paper compares the performance of tracking portfolios formed out of the assets belonging to one of the 10 investment categories in the presence of transaction costs that are otherwise an inescapable element of investing. Although limited by the choice of the time frame for the experiment, the paper finds that linear tracking is preferable over quadratic tracking as it is both associated with smaller transaction costs and with generally better performance. Nonetheless, it is very difficult to state firm conclusion as the pattern changes during the investigated time frame. The first two samples defined over the time frame under consideration would favour small capitalization portfolios, this is no longer true for the last sample where there is mixed evidence regarding the investment style and the size of pre-selection.

The remainder of the paper is made up of five more sections. The following two sections are expository – they explain and contrast investment styles that are applicable in equity investing, and summarize the technicalities of portfolio tracking alongside the model of transaction costs, respectively. The other two sections give a description of the experimental design and organize the results. Eventually, the last section concludes and discusses.

Investment styles

Adhering to a certain investment style means favouring a specific category of assets over another and designating the assets for this category as fit candidates for portfolio construction. Historically, these categories were identified as clusters of stocks with similar characteristics and performance patterns and are now associated with a "style" of investing (see Fabozzi, 1998, p. 57). It has become a standard to classify assets according to their market capitalization and value/growth potential into: (a) large size, (b) small size, (c) large value and small growth, (d) small value and large growth.

The first criterion for setting up the categories by size is market capitalization. This is sort of historical as the past studies of stock returns established that "smaller is better" and that stocks with the lowest market capitalization tend to deliver the highest returns. The reason being, smaller firms are more agile and are still possibly capable of accelerated growth owing to their small size. Another aspect is that small capitalization stocks are more risky and plagued with higher price volatility since smaller firms have fewer resources and operate less diversified business segments. On the other hand, large capitalization stocks have a greater say in the market movement and they are represented by a higher weight in a market index. If the intention is to track this market index (hoping that it will prevent under-performance from happening), it is reasonable to choose especially from such stocks. Moreover, there are cycles at the market when these large cap stock constantly out-perform small cap stocks. There are sound reasons to opt for either of these two categories, but perhaps a conservative investor would feel safer with large cap stocks unlike a risk seeking investor who would appreciate investing into small cap stocks. To implement this classification means to order assets by their market capitalization and split them midway around the 50% quantile. The result is small cap stocks ("S") and big cap stocks ("B")

The second criterion that distinguishes between value and growth assets rests upon using a suitable financial indicator. Growth investment style focuses upon stocks of firms with high growth potential (concerning earnings) and with high return on equity, profit margins and low dividend yields. On the contrary, value investment style is concerned with well-established firms with a good price. Such firms have usually low P/E (price to earnings) ratio or low profit margins offset by a higher dividend yield. An example of a value/growth classification indicator is the P/B (price to book value per share) ratio as advocated by Fama and French (1993). Growth stocks pertain to firms with higher earnings (as a mere consequence of growth) that imply higher book value. The stock price must also rise so that the P/B ratio remains unchanged. A high value of the P/B ratio is just an indication of high growth potential. Conversely, value stocks are of those firms that attain lower earnings and are such that they preserve their market prices (and also value), which means the their P/B ratio must be relatively small. Fabozzi (1998, p. 60) suggests a procedure for classifying stocks by value and growth that consists in ordering stocks first by their P/B ratios and then dividing them into two classes by their accumulated market capitalization. Stocks whose accumulated market capitalization does not exceed 50% are pronounced as value stocks ("V") and those on the other side of the ordered axis are viewed as growth stocks ("G").

Finally, there is a possibility to combine these two criteria as suggested by Fama and French (1993) in a context of performance analytics. They split assets along size and value/growth dimensions with the aid of market capitalization and the P/B ratio. They suggested dividing stocks by median market capitalization according to which the first half of stocks with the lowest capitalization is classified as small cap stocks ("S") and the remainder is singled out as big cap stocks ("B"). Stocks are simultaneously sorted by their P/B ratios. The bottom 30% are classified as high ("H"), the middle 40% as medium ("M") and the left 30% as low ("L"). These two concurrent splits lead to six stock categories: "BH", "BM", "BL", "SH", "SM" and "SL" stocks. The usability of this approach for performance analysis is detailed in the original cited paper or in Grinold and Kahn (2000, p. 496–497).

Linear and quadratic portfolio tracking

The conventional model of portfolio tracking is in the paper applied both in a linear variant and in a quadratic setting, and is further extended by a model of charging transaction costs in which the full budget available for investment is exhausted. The optimization model does not take into account transaction costs that arise with creation of a particular portfolio – they are calculated ex post and paid only at the moment of acquiring the asset holdings of the optimized portfolio.

For presentational purposes, it is assumed that T historical observations of (preferably logarithmic) returns are available and that k assets are pre-selected for portfolio tracking. Let Y_t, $x_{1,t}$,..., $x_{k,t}$ denote the benchmark return and k asset returns at time t, respectively, wherein $t \in \{1,...,T\}$. The unknown portfolio weights ω_1,..., ω_k are determined either by solving (a linear equivalent of) the non-linear optimization problem (a.k.a. linear tracking)

$$\min_{\omega_1,...,\omega_k \in \Re} \frac{1}{T} \sum_{t=1}^{t=T} \left| Y_t - \sum_{r=1}^{r=k} \omega_r x_{r,t} \right|$$
$$\text{s. t.} \quad \sum_{r=1}^{r=k} \omega_r = 1 \quad \text{and possibly other constraints,} \quad (1)$$

or by implementing (an equivalent to) the quadratic optimization problem (a.k.a. quadratic tracking)

$$\min_{\omega_1,...,\omega_k \in \Re} \frac{1}{T} \sum_{t=1}^{t=T} \left(Y_t - \sum_{r=1}^{r=k} \omega_r x_{r,t} \right)^2$$
$$\text{s. t.} \quad \sum_{r=1}^{r=k} \omega_r = 1 \quad \text{and possibly other constraints.} \quad (2)$$

The general formulation of (1) and (2) permits an extension and can be complemented by the constraint banning short sales requiring that ω_1,..., $\omega_k \geq 0$. This constraint is also employed here in the analysis and only long positions are sought, although also other constraints may be (and are) encountered in practice. Note that the expression to be optimized in (1) is just the mean absolute error, whereas the one in (2) is the mean square error. A useful commentary on the computational aspects of (1) and (2) is provided by Rudolf, Wolter and Zimmermann (1999).

The model of charging transaction costs begins with a budget B available for the investment and stipulates two form of transaction costs for an investor. Both of them are variable transaction costs; some transaction costs are applied to the number of assets bought or sold for the portfolio and some pertain to the number of asset holds that arise therewith. The lump charges of variable costs are denoted as χ_A per asset traded and χ_H per holding of an asset purchased or sold. Assume that the optimal solution $\omega_1^{\#}$,..., $\omega_k^{\#}$ to (1) or (2) with an added ban on short sales comprises $k^{\#}$ non-zero weights and that the prices of assets at the moment of portfolio creation are P_1,..., P_k. The variable costs then follow from the reckoning, $B^{\S} = B - k^{\#} \cdot \chi_A - \chi_H \cdot \Sigma |B^{\S} \cdot \omega_i^{\#}/P_i|$, in which the sum available for investment, B, is taken off by the total of variable costs, $k^{\#} \cdot \chi_A + \chi_H \cdot \Sigma |B^{\S} \cdot \omega_i^{\#}/P_i|$, and the effective amount of investment, $B^{\S}$, is obtained as a result. Here $B^{\S} \cdot \omega_i^{\#}/P_i$ denotes the holdings of an i-th asset and they derive from the actual sum, $B^{\S}$, that can be allocated to the investment after satisfying all the transactions costs applicable. The equation can be straightforward solved for $B^{\S}$. It is also possible to accommodate other forms of transaction costs, but the present considerations should be sufficient to map the effect of transaction costs upon performance. For instance, fixed transaction costs simply lower the initial budget available for investment.

Experimental set-up

The analysis assumes that the investor wishes to track the S & P 500 Index by virtue of a portfolio formed out of no more than 50 stocks selected from the basket of about 500 constituents represented in the index. To this end, he uses historical logarithmic returns of a weekly frequency for a period of two years (the in-sample period) that provide an input to the optimization model as given in (1) and (2), and on the basis of the identified optimal weights he creates a portfolio on the last day of the in-sample period that coincides with the end of a year. The situation is somewhat simplified because he holds the portfolio for at least one year to come (the out-of-sample period) without any thought about it rebalancing or dismissal. Never the less, the hypothesized situation of buying a portfolio and holding it for a year is still capable of providing a valuable insight into the attractiveness of pre-selection process. In point of fact, it affords an opportunity to assess the possibility to construct the tracking portfolio with (one-year or shorter-than-one-year) good performance on the first try.

A total of three samples are created as indicated in Tab. I. Sample 1 has the in-sample period covering 2011 and 2012 and the out-of-sample period is 2013, then a one-year window is slid twice until Sample 3 has the in-sample period spanning 2013 and 2014 and the out-of-sample period is 2015. These time spans suggest 105 effective in-sample returns for Sample 1 and 104 effective in-sample returns for Samples 2 and 3, whereas for the out-of-sample period 52 observation in each sample.

The moment of portfolio creation is also promulgated in Tab. I, and this represents the reference day to which the S & P 500 Index is scanned for its constituents. The basket of effective constituents that can take part in the exercise is limited by the availability of data. Some stocks represented in the index at the end of the in-sample period did not have a sufficiently long history to be contained fully in the in-sample and out-of-sample period. The reason being, some stocks were too fresh and were only newly added to the index in the in-sample period, whilst others were relieved from the index during the out-sample period (e.g. in consequence of a merge). The basket of effective S & P 500 Index constituents was with each sample divided into 10 categories. Using the P/B ratio, the procedure advertised by Fabozzi (1998, p. 60) divided the S & P 500 Index constituents into value stocks ("V") and growth stocks ("G"). According to this procedure, stocks were first sorted from the lowest P/B ratio to the highest P/B ratio, and then the lowest P/B stocks up to the point of about 50% of accumulated market capitalization were declared as value stocks and the remaining stocks were recognized as growth stocks. The classification espoused by Fama and French (1993) distinguishes as many as two plus six categories. The median market capitalization known at the day of portfolio creation was used to classify the S & P 500 Index constituents into big cap stocks ("B") and small cap stocks ("S"). In addition, all the S & P 500 Index constituents were sorted by the P/B ratio. the top 30% were classified as high ("H"), the middle 40% were classifies as medium ("M") and the bottom 30% as low ("L"). These two splits led to six portfolios: "BH", "BM", "BL", "SH", "SM" and "SL". The stratification of these stock categories corresponding to different investment styles is displayed in Tab. II for each sample.

I: *Definition of the three samples*

	2011	2012	2013	2014	2015
Sample 1	In-sample period [portfolio creation as of 31 Dec 2012]		Out-of-sample period		
Sample 2		In-sample period [portfolio creation as of 30 Dec 2013]		Out-of-sample period	
Sample 3			In-sample period [portfolio creation as of 29 Dec 2014]		Out-of-sample period

Source: the authors.

II: *Sizes of investment style stratas in the samples*

	Fama-French classification						Value/growth stocks	
	Big capitalization stocks			Small capitalization stocks				
	BH	BM	BL	SH	SM	SL	V	G
Sample 1		226			213		240	199
	59	100	67	70	76	67		
Sample 2		231			221		241	211
	57	103	71	74	80	67		
Sample 3		234			224		248	210
	61	97	76	72	89	63		

Source: the authors.

The big capitalization stocks (falling into the "B", "BH", "BM", "BL" categories) and small capitalization stocks (falling into the "S", "SH", "SM", "SL" categories) were naturally ordered by market capitalization descending and ascending, respectively. The value and growth stocks (in the "V" and "G" categories) were ordered by the P/B ratio in a similar manner. Respecting this natural ordering, subsets of 10, 20, 30, 40 and 50 stocks were picked step-wise from these 10 investment style categories as the candidate assets for tracking portfolios targeted at the S & P 500 Index. Considering 5 sizes of small portfolios and 10 investment styles reflected in asset pre-selection, there were a total of 5 × 10 = 50 portfolios for which both linear and quadratic tracking were conducted for comparison.

The usefulness of the 10 investment styles was evaluated in the presence of transaction costs with the budget available for investment B = US$ 10,000, the amount of variable transaction costs χ_A = US$ 5 per one unit of asset acquired, and the lump amount χ_H = US$ 0.1 per unit of asset holding acquired. This configuration was designed to be helpful in mimicking the actual (non-experimental) conditions in which portfolios are formed.

The results are presented in the next section. In computations and preparing graphical presentations, the software R version 3.0.1 (R Core Team, 2013) was employed with several of its libraries, lpSolve (Berkelaar *et al.*, 2015), quadprog (Turlach and Weingessel, 2013) and timeSeries (Wuertz and Chalabi, 2013).

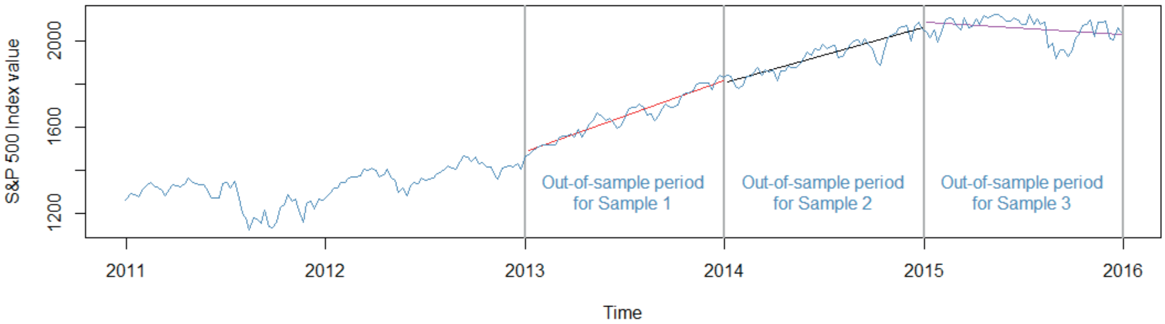
RESULTS

Success of portfolio tracking can be assessed by using diverse criteria and understood in terms of either terminal portfolio values or average portfolio returns, though in either case relative to the benchmark. In the former case, portfolio values must be confronted against values of the equivalent fictional investment into the selected benchmark. It is then interesting to examine how often or how long in the out-of-sample period values of the tracking portfolio exceeded values of the fictional investment into the benchmark. In the latter case, viz. if performance is assessed through returns, active returns are constructed as portfolio returns minus benchmark returns. What is studied is their mean (i.e. mean active returns) or their mean relative to standard deviation (i.e. the information ratio). This is reported in Tabs. III to V in Appendix A for any portfolio constructed by combining the nominal size (10, 20, 30, 40 and 50 stocks) and the investment style ("B", "BH", "BM", "BL", "S", "SH", "SM", "SL", "V","G"). These tables exhibit mean active returns, information ratios and percentages by which a tracking portfolio outperformed the underlying S & P 500 Index. In addition, they display effective numbers of assets $k^{\#}$ in constructed portfolios (taking into account that some stocks might have been given a zero weight) and also percentages of transaction costs that apply.

Irrespective of the sample under consideration and the tracking method, transaction costs are a monotonous function of the portfolio size. For portfolios of nominal size 10 assets they typically range between 0.5% and 1% of the invested amount, whereas for portfolios selected from 50 assets they are about 2% (with linearly tracked portfolios) or even well above 2% (with quadratically tracked portfolios). In the vast majority of cases, linear tracking yields lower transaction costs than quadratic tracking does, and this difference is on average about 0.30% of the initial sum invested and sometimes it reaches to 1%.

The superiority of some investment styles is exhibited in the figures organized in Appendix B. These figures localize individual tracking portfolios in terms of their mean active returns and performance measured by their information ratios. In order to make the scatter graphs in Appendix B informative, two scatter graphs are produced and juxtaposed (those on the left for "B", "S", "V" and "G" portfolios, and those on the right for Fama-French portfolios). For Samples 1 and 2 there is no material difference between linearly and quadratically tracked portfolios. Differences only appear with Sample 3. For Sample 1 (Figs. 2a and 2b), the small capitalization investment style seems to yield the best-performing tracking portfolios, it is especially the case of "S" portfolios with 10 and 20 assets pre-selected or "SH" portfolios with 30, 40 or 50 assets pre-selected. For Sample 2 (Figs. 3a and 3b), the best-performers are again the "S" portfolios with 10 and 20 assets pre-selected or the "SH" portfolios with any number of pre-selected assets. In addition, the ranks of these portfolios are now enlarged also by the value oriented investment style as the "V" portfolios with 20 to 50 assets pre-selected have a very similar performance profile (viz. a high mean active return and a high information ratio) as the "S" portfolios. Oddly enough, contrary evidence is gathered for Sample 3 (Figs. 4a and 4b), in which case the best-performing investment styles are more varied. The best performance profile is for Sample 3 shared by the "G" portfolios with about 20 to 40 assets pre-selected, the "B" and "SM" portfolios with pre-selected 30 assets, and the "BL" portfolios with pre-selection of 10 and 20 assets. The finding is that good performance is dispersed across different ends of the investment style spectrum without any apparent regularity. The universal pattern indicated for Samples 1 and 2 is thus defied.

Finally, another appealing aspect is the percentage of weeks of the out-of-sample period in which the tracking portfolio outperforms the fictional investment into the benchmark index. By comparing the percentages in Tabs. III to V, it becomes evident that the method of linear tracking is perhaps more contributive to out-performance than the method of quadratic tracking because portfolios with this percentage above 50% with some rare exceptions are more frequent (and even greater). This "out-performance percentage" of performance is important since the investment horizon need not be exactly one year and in actual fact the investor may choose to invest for a shorter time horizon than one year. It is very unlikely that he would keep his portfolio unchanged and would not rebalance after one year of holding. If this percentage is high, there is no need to rebalance and the tracking portfolio may be left unchanged, which is obviously a desirable circumstance. Sticking to the percentages for linearly tracked portfolios, the best out-performers for Sample 1 were the "S" portfolios with 10 to 30 assets pre-selected (about 94 and 96%), the "SH" portfolios with 30 to 50 assets (about 94%) and the "SL" portfolio with 10 assets (about 89%). For Sample 2, the highest out-performance percentages were ascertained with the "SH" portfolios (about 94 or 96% for 10 to 40 assets pre-selected and about 89% for 50 assets pre-selected). Eventually, for Sample 3, the highest percentage of cases when the tracking portfolio had a higher value than the index was only the "BL" portfolio with 10 assets (about 91%). In this particular case, if the tracked portfolio were optimized under quadratic tracking, the percentage would be even 98%. The pattern that was detected for Samples 1 and 2 and suggested a preference for small capitalization portfolios was changed and lost for Sample 3.



1: *S & P 500 Index over the entire time-frame from 2011 to 2015*
Source: the authors.

CONCLUSION

The paper targeted at usefulness of conventional investment styles in asset pre-selection necessary for portfolio tracking in conditions of a small investor who cannot afford to set up a large scale portfolio whose creation and maintenance would incur high transaction costs. In the experimental design of tracking the S & P 500 index in three consecutive two-plus-one-year sub-periods spanning from 2011 until 2015, stocks representing constituents of this index were differentiated by market capitalization into small cap stocks ("S") and big cap stocks ("B") and by the P/B ratio into value stocks ("V") and growth stocks ("G"). This categorization was further extended by double stratification by these criteria in the style of Fama and French (1993), which gave rise to the categories "BH", "BM", "BL", "SH", "SM", "SL". The performance of both linearly and quadratically tracked portfolios was evaluated with respect to the information ratio and the percentage of cases in which the tracking portfolio outperforms the index. For each portfolio, only 10, 20, 30, 40 or 50 stocks were pre-selected as candidates for portfolio creations and the investment was made no longer than for a year. Of course, the snapshot of the present analysis and the sole focus upon the S & P 500 Index does not permit a satisfactory level of generalization, but the results are still insightful for small investors concerning their best strategies. In spite of this bold statement, the results are affected by the instability of market patterns as it turns out. On one hand, for the first two samples, Samples 1 and 2 (with the years 2013 and 2014 as the investment out-of-sample periods, respectively), small cap portfolios were found prevailing in terms of both in-sample performance (represented by the information ratio and its relationship to the mean active returns) and out-of-sample performance (measured by the percentage of weeks in the out-of-sample period in which the tracking portfolio fares better than the index). This tendency was systematic and would promote tracking portfolios composed of purely small cap stocks or those small cap stocks that reveal growth-tending features (represented by a high P/B ratio). On the other hand, this pattern was destroyed in the last sample, Sample 3 (having the year 2015 as the investment out-of-sample period), in which no preferable properties of such portfolios were observed. Only one portfolio might be looked upon as to deliver extraordinary performance and this was the tracking portfolio made up of 10 large cap stocks with value-preserving potential (measured by a low P/B ratio). This is but a completely opposite pattern that challenges the advisability of small cap (possibly value warranting) stocks for pre-selection in portfolio tracking.

The reasons are discernible in Fig. 1 that shows the S & P 500 Index values over the time frame under investigation with the out-of-sample periods representing investment horizons for each of Samples 1 to 3. Whereas in 2013 and 2014 (the investment periods for Samples 1 and 2) the index steadily grew without any relevant flaw in the development pattern, in 2015 it levelled off and tended to slope somewhat downwards. This is confirmed by line segments that were fitted by standard regression separately for each window separated by gray vertical lines. The line segments for Sample 1 and 2 almost connect without a change; the change is apparent and noticeable for 2015 representing the investment horizon of Sample 3. In other words, the underlying S & P 500 Index changed its direction and indicates a change in market trends and the market situation. Small cap stocks are associated with strong growth potential, and therefore they are better suited to pick up rising tendencies exhibited in 2013 and 2014, and they are obviously recommendable for situations when the market is (expected to be) on the up-swing. However, when the market is bearish, possibly big cap stocks might be more appealing.

These findings merely testify the fact that different investment styles are associated with different life cycles. Boudt and Peeters (2013) provide evidence that low risk portfolios report smaller losses on bear markets and smaller gains on bull markets than market indexes do. Value style investment strategies tend to generate higher gains during bull markets and to moderate losses in the times of bear markets. A combination of these two investment styles might possibly help to lessen or eliminate the dependence of portfolio returns upon the market regime whereas keeping attractive performance and a good balance between return and risk. The observation of these authors that "by combing value and low risk investment styles into a smart single portfolio the individual life cycle of each strategy is diversified away into 'stable' out-performance" is also appealing also for the present case. The present findings may be further extended by merging small cap (or small cap and growth) investment styles that fare better during a bull market with big cap (or big cap and value) investment styles that display better behaviour during a bear market.

An important side effect of the study is the observed superiority of linear tracking over quadratic tracking. When comparing the transactions costs and percentage of out-performance cases, linearly tracked portfolios on average seem cheaper and more reliable.

A natural avenue for further research is to extend the analysis to accommodate a longer period of time, to allow various modes of rebalancing and to consider also other market, not only the case of the U.S. market with the S & P 500 Index. Another option to implement is to rank assets within each group of candidate assets by means of the P/S (price to sales) ratio as recommended by Barbee *et al.* (1996) and Gold and Lebowitz (1999). For portfolio tracking under this criterion qualify assets from a designated group with lower values of the P/S ratio. There, of course, are economic reasons that support this indicator, but one attractive trait is its mathematical convenience as it can never happen to be negative.

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REFERENCES

BARBEE, W. C., MUKHERJI, S. and RAINES, G. A. 1996. Do soles-price and debt-equity explain stock returns better than book-market and firm size? *Financial Analysts Journal* 3(4): 56–60.

BARBERIS, N. and SCHLEIFER, A. 2003. Style investing. *Journal of Financial Economics* 68(2): 161–199.

BERKELAAR, M. et al. 2015. *lpSolve: interface to 'Lp_solve' v. 5.5 to solve linear/integer programs.* R package, version 5.6.13. [Online]. Available at: http://cran.r-project.org/web/packages/lpSolve/index.html [Accessed: 2017, January 31].

BOUDT, K. and PEETERS, B. 2013. *Smart harvesting of equity style premia.* Finvex fourth white paper. Finvex Group. [Online]. Available at: http://finvex.com/awards [Accessed: 2017, January 31].

CHAN, L.,CHEN, H. and LAKONISHOK, J. 2002. On mutual fund investment styles. *Review of Financial Studies*, 15(5): 1407–1437.

DE LONG, J. B., SCHLEIFER, A., SUMMERS, L., and WALDMANN, R. 1990. Positive feedback investment strategies and destabilising rational speculation. *Journal of Finance*, 45(2): 375–395.

FABOZZI, F. J. 1998. Overview of equity style management. In: FABOZZI, F. J. (Ed.). *Active equity portfolio management.* New Hope (PA): Frank J. Fabozzi Associates, pp. 57–70.

FABOZZI, F. J. 2002. *The handbook of financial instruments*. New Jersey : Wiley.

FAMA, E. F. and FRENCH, K. R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1): 3–56.

FARRELL, J. L. JR. 1975. Homogenous stock groupings: implications for portfolio management. *Financial Analysts Journal*, 31(3): 50–62.

GOLD, S. C. and LEBOWITZ, P. 1999. Computerized stock screening rules for portfolio selection. *Financial Services Review*, 8(2): 61–70.
GRINOLD, R. C. and KAHN, R. N. 2000. *Active portfolio management.* 2nd Edition. New York: McGraw-Hill.
HONG, H. and STEIN, J. 1999. A unified theory of underreaction, momentum trading and overreaction in asset markets. *Journal of Finance*, 54(6): 2143–2184.
R CORE TEAM. 2013. *R: a language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing.
RUDOLF, M., WOLTER, H.-J. and ZIMMERMANN, H. 1999. A linear model for tracking error minimization. *Journal of Banking & Finance*, 23(1): 85–103.
SCHADLER, F. P. and EAKINS, S. G. 2001. A stock selection model using Morningstar's style box. *Financial Services Review*, 10(1–4): 129–144.
TURLACH, B. A. and WEINGESSEL, A. 2013. *quadprog: functions to solve quadratic programming problems.* R package, version 1.5-5. [Online]. Available at: http://cran.r-project.org/package=quadprog [Accessed: 2017, January 31].
WUERTZ, D. and CHALABI, Y. 2013. *timeSeries: Rmetrics – financial time series objects.* R package, version 3010.97. [Online]. Available at: http://cran.r-project.org/web/packages/timeSeries/index.html [Accessed: 2017, January 31].

Appendix A

III: *Performance and portfolio selection statistics for Sample 1*

Style & # assets		Linear tracking					Quadratic tracking				
		Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index
B	**10**	–0.002	–0.236	10	0.69%	0.00%	–0.001	–0.188	10	0.69%	0.00%
B	**20**	–0.002	–0.332	18	1.11%	0.00%	–0.001	–0.303	20	1.23%	0.00%
B	**30**	0.000	–0.121	27	1.59%	0.00%	–0.001	–0.201	30	1.73%	0.00%
B	**40**	0.000	–0.021	37	2.05%	0.00%	0.000	–0.023	39	2.16%	0.00%
B	**50**	0.000	–0.140	43	2.34%	0.00%	0.000	–0.095	49	2.64%	0.00%
S	**10**	0.004	0.282	9	0.94%	94.34%	0.004	0.301	10	0.95%	94.34%
S	**20**	0.004	0.337	13	0.99%	94.34%	0.004	0.357	19	1.29%	94.34%
S	**30**	0.001	0.190	20	1.34%	96.23%	0.002	0.206	29	1.80%	94.34%
S	**40**	0.001	0.079	23	1.53%	64.15%	0.001	0.097	39	2.33%	54.72%
S	**50**	0.001	0.086	24	1.58%	73.58%	0.001	0.108	50	2.89%	49.06%
V	**10**	–0.001	–0.187	9	0.73%	0.00%	–0.002	–0.216	10	0.77%	0.00%
V	**20**	0.000	–0.022	18	1.16%	0.00%	0.000	–0.049	19	1.23%	0.00%
V	**30**	0.000	–0.030	23	1.40%	3.77%	0.000	–0.069	29	1.71%	0.00%
V	**40**	–0.001	–0.103	33	1.89%	0.00%	–0.001	–0.155	39	2.19%	0.00%
V	**50**	0.000	–0.053	32	1.82%	1.89%	0.000	–0.061	48	2.63%	0.00%
G	**10**	–0.002	–0.174	8	0.60%	0.00%	–0.002	–0.187	9	0.64%	0.00%
G	**20**	0.000	–0.083	16	0.96%	0.00%	0.000	–0.043	19	1.10%	11.32%
G	**30**	0.000	–0.100	24	1.34%	0.00%	0.000	–0.111	29	1.59%	0.00%
G	**40**	0.000	–0.088	30	1.65%	0.00%	–0.001	–0.174	39	2.11%	0.00%
G	**50**	0.000	–0.065	33	1.79%	0.00%	0.000	–0.123	50	2.66%	0.00%
BH	**10**	0.000	–0.048	9	0.65%	22.64%	0.000	–0.055	10	0.68%	33.96%
BH	**20**	0.000	0.097	14	0.88%	77.36%	0.000	0.080	19	1.12%	77.36%
BH	**30**	0.000	0.070	19	1.14%	79.25%	0.000	0.058	30	1.70%	54.72%
BH	**40**	0.001	0.112	23	1.35%	71.70%	0.001	0.124	39	2.16%	33.96%
BH	**50**	0.000	0.035	29	1.66%	22.64%	0.001	0.130	49	2.67%	24.53%
BM	**10**	–0.001	–0.139	9	0.70%	7.55%	–0.001	–0.124	10	0.75%	1.89%
BM	**20**	0.000	0.040	19	1.17%	11.32%	0.000	0.042	19	1.18%	24.53%
BM	**30**	0.000	–0.054	27	1.59%	0.00%	0.000	–0.082	30	1.74%	0.00%

Style & # assets	Linear tracking					Quadratic tracking				
	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index
BM 40	0.000	–0.119	36	2.03 %	0.00 %	0.000	–0.132	39	2.18 %	0.00 %
BM 50	0.000	–0.099	36	2.03 %	0.00 %	0.000	–0.072	50	2.73 %	0.00 %
BL 10	–0.002	–0.249	9	0.61 %	0.00 %	–0.002	–0.227	10	0.65 %	0.00 %
BL 20	0.001	0.102	12	0.73 %	35.85 %	0.000	0.071	20	1.13 %	18.87 %
BL 30	0.000	0.074	20	1.13 %	50.94 %	0.000	0.050	30	1.63 %	7.55 %
BL 40	0.000	0.050	21	1.19 %	20.75 %	0.000	0.054	39	2.09 %	0.00 %
BL 50	0.000	–0.085	26	1.45 %	0.00 %	0.000	–0.086	49	2.59 %	0.00 %
SH 10	–0.001	–0.115	10	0.73 %	11.32 %	–0.001	–0.098	10	0.72 %	7.55 %
SH 20	0.000	0.014	16	1.02 %	62.26 %	0.000	0.031	19	1.19 %	54.72 %
SH 30	0.002	0.314	21	1.46 %	94.34 %	0.002	0.285	29	1.84 %	88.68 %
SH 40	0.001	0.282	29	1.78 %	94.34 %	0.001	0.245	39	2.31 %	92.45 %
SH 50	0.001	0.230	31	1.87 %	94.34 %	0.001	0.234	50	2.84 %	92.45 %
SM 10	0.000	0.042	10	0.79 %	83.02 %	0.000	0.019	10	0.75 %	75.47 %
SM 20	0.000	0.009	17	1.11 %	67.92 %	0.000	–0.014	19	1.19 %	66.04 %
SM 30	0.000	–0.016	22	1.37 %	69.81 %	0.000	–0.076	29	1.70 %	54.72 %
SM 40	0.000	–0.030	27	1.64 %	62.26 %	0.000	–0.029	39	2.22 %	32.08 %
SM 50	0.000	–0.002	33	1.94 %	62.26 %	0.000	–0.056	49	2.71 %	9.43 %
SL 10	0.001	0.119	9	0.71 %	88.68 %	0.001	0.102	9	0.71 %	88.68 %
SL 20	–0.001	–0.080	14	0.92 %	58.49 %	–0.001	–0.092	19	1.17 %	64.15 %
SL 30	–0.001	–0.102	22	1.29 %	11.32 %	0.000	–0.031	29	1.66 %	73.58 %
SL 40	–0.001	–0.095	25	1.44 %	16.98 %	0.000	–0.031	39	2.15 %	32.08 %
SL 50	–0.001	–0.137	34	1.90 %	0.00 %	–0.001	–0.076	50	2.70 %	0.00 %

Source: the authors.

IV: *Performance and portfolio selection statistics for Sample 2*

Style & # assets	Linear tracking					Quadratic tracking				
	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index
B 10	–0.002	–0.176	10	0.66 %	11.32 %	–0.002	–0.185	10	0.65 %	15.09 %
B 20	–0.002	–0.244	17	1.03 %	0.00 %	–0.003	–0.226	18	1.05 %	0.00 %
B 30	–0.002	–0.175	29	1.62 %	0.00 %	–0.002	–0.188	29	1.62 %	0.00 %
B 40	–0.002	–0.265	31	1.70 %	0.00 %	–0.002	–0.262	39	2.10 %	0.00 %
B 50	–0.001	–0.154	39	2.12 %	0.00 %	–0.002	–0.192	49	2.60 %	0.00 %
S 10	0.000	0.041	9	0.74 %	69.81 %	0.000	0.031	9	0.75 %	67.92 %
S 20	–0.001	–0.077	16	1.12 %	0.00 %	–0.001	–0.083	19	1.30 %	0.00 %
S 30	0.000	–0.058	20	1.33 %	0.00 %	0.000	–0.072	30	1.84 %	0.00 %
S 40	0.000	–0.051	21	1.35 %	0.00 %	0.000	–0.064	39	2.26 %	0.00 %
S 50	0.000	0.075	26	1.59 %	18.87 %	0.000	0.035	49	2.75 %	0.00 %
V 10	–0.002	–0.268	10	0.69 %	0.00 %	–0.002	–0.292	9	0.64 %	0.00 %
V 20	0.000	–0.049	19	1.19 %	16.98 %	0.000	0.020	19	1.16 %	28.30 %
V 30	0.000	0.012	25	1.47 %	0.00 %	0.000	–0.013	28	1.62 %	0.00 %
V 40	0.000	–0.002	32	1.80 %	0.00 %	0.000	–0.035	39	2.15 %	0.00 %
V 50	0.000	0.013	32	1.79 %	0.00 %	0.000	–0.024	49	2.64 %	0.00 %
G 10	–0.002	–0.192	9	0.58 %	9.43 %	–0.002	–0.175	9	0.57 %	13.21 %
G 20	–0.002	–0.211	18	1.02 %	0.00 %	–0.003	–0.225	20	1.11 %	0.00 %
G 30	–0.002	–0.158	27	1.47 %	0.00 %	–0.003	–0.190	29	1.57 %	0.00 %

Style & # assets	Linear tracking					Quadratic tracking				
	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index
G 40	–0.002	–0.146	28	1.52%	0.00%	–0.002	–0.152	40	2.12%	0.00%
G 50	–0.002	–0.174	35	1.87%	0.00%	–0.002	–0.171	49	2.57%	0.00%
BH 10	–0.002	–0.201	7	0.51%	1.89%	–0.002	–0.215	9	0.60%	1.89%
BH 20	–0.002	–0.274	15	0.92%	0.00%	–0.002	–0.261	19	1.11%	0.00%
BH 30	–0.001	–0.171	21	1.22%	0.00%	–0.001	–0.197	29	1.62%	0.00%
BH 40	–0.001	–0.154	24	1.38%	16.98%	–0.001	–0.143	39	2.13%	1.89%
BH 50	–0.001	–0.158	28	1.59%	15.09%	–0.001	–0.152	49	2.63%	0.00%
BM 10	–0.002	–0.175	10	0.69%	16.98%	–0.003	–0.180	10	0.68%	16.98%
BM 20	–0.001	–0.154	17	1.03%	16.98%	–0.001	–0.175	20	1.18%	16.98%
BM 30	–0.001	–0.102	26	1.47%	20.75%	–0.001	–0.076	29	1.62%	20.75%
BM 40	–0.001	–0.102	32	1.76%	11.32%	–0.001	–0.101	39	2.12%	1.89%
BM 50	–0.002	–0.164	42	2.27%	0.00%	–0.001	–0.125	49	2.62%	0.00%
BL 10	–0.004	–0.220	9	0.53%	0.00%	–0.003	–0.213	9	0.54%	0.00%
BL 20	–0.003	–0.239	16	0.91%	0.00%	–0.002	–0.221	19	1.06%	0.00%
BL 30	–0.001	–0.099	24	1.32%	0.00%	–0.001	–0.093	29	1.57%	0.00%
BL 40	–0.001	–0.183	27	1.47%	0.00%	–0.001	–0.227	39	2.06%	0.00%
BL 50	–0.001	–0.190	35	1.88%	0.00%	–0.001	–0.160	49	2.58%	0.00%
SH 10	0.002	0.206	9	0.61%	96.23%	0.002	0.187	9	0.61%	96.23%
SH 20	0.002	0.277	17	1.16%	96.23%	0.002	0.296	19	1.26%	96.23%
SH 30	0.002	0.315	24	1.47%	94.34%	0.002	0.318	29	1.77%	94.34%
SH 40	0.002	0.288	27	1.64%	94.34%	0.001	0.264	39	2.25%	92.45%
SH 50	0.001	0.238	32	1.98%	88.68%	0.001	0.143	49	2.77%	35.85%
SM 10	0.000	–0.083	9	0.70%	0.00%	0.000	–0.036	10	0.74%	0.00%
SM 20	–0.001	–0.146	18	1.12%	0.00%	0.000	–0.078	19	1.17%	0.00%
SM 30	–0.001	–0.097	23	1.35%	0.00%	0.000	–0.058	29	1.64%	0.00%
SM 40	–0.001	–0.194	24	1.36%	0.00%	–0.001	–0.201	39	2.12%	0.00%
SM 50	–0.001	–0.104	36	2.00%	5.66%	–0.001	–0.139	49	2.64%	0.00%
SL 10	–0.003	–0.245	9	0.62%	0.00%	–0.002	–0.200	10	0.66%	0.00%
SL 20	–0.002	–0.229	16	0.94%	0.00%	–0.002	–0.278	19	1.09%	0.00%
SL 30	–0.001	–0.186	20	1.15%	0.00%	–0.001	–0.170	29	1.60%	0.00%
SL 40	–0.001	–0.074	27	1.51%	9.43%	0.000	–0.051	39	2.10%	0.00%
SL 50	0.000	0.007	28	1.57%	11.32%	0.000	–0.046	49	2.61%	0.00%

Source: the authors.

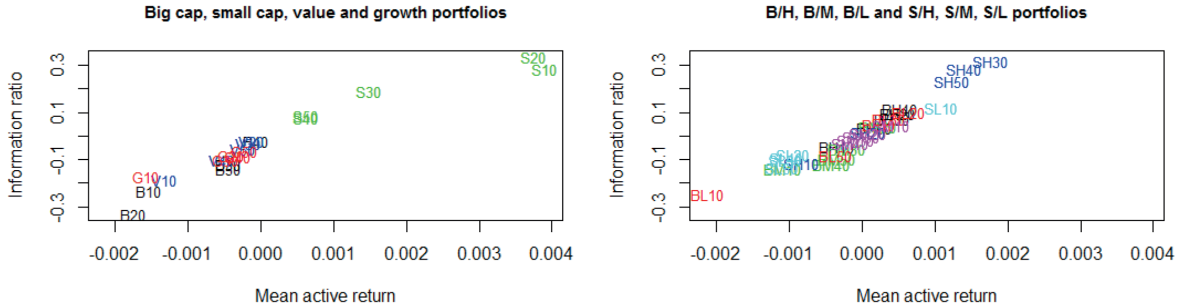
V: *Performance and portfolio selection statistics for Sample 3*

Style & # assets	Linear tracking					Quadratic tracking				
	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index
B 10	0.000	0.053	10	0.68%	9.43%	0.000	0.048	10	0.68%	7.55%
B 20	0.000	–0.008	17	1.06%	0.00%	0.000	0.023	19	1.16%	1.89%
B 30	0.001	0.197	25	1.43%	24.53%	0.001	0.163	30	1.69%	22.64%
B 40	0.000	0.029	30	1.66%	0.00%	0.000	0.069	39	2.12%	0.00%
B 50	0.000	0.067	39	2.10%	1.89%	0.000	0.009	49	2.61%	0.00%
S 10	–0.006	–0.251	9	0.83%	18.87%	–0.007	–0.278	9	0.84%	15.09%
S 20	–0.001	–0.106	13	1.03%	5.66%	0.000	–0.020	19	1.29%	33.96%
S 30	0.000	–0.034	20	1.32%	11.32%	0.000	–0.017	29	1.80%	28.30%

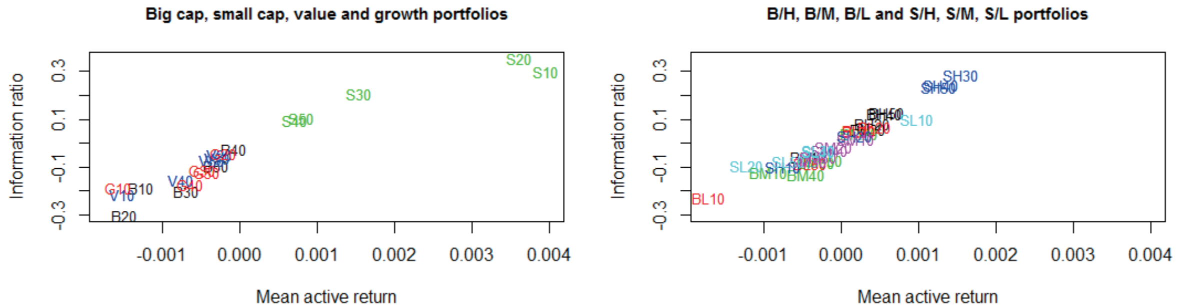
Style & # assets		Linear tracking					Quadratic tracking				
		Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index	Mean active returns	Information ratio	Eff # assets	% trading costs	% better than the index
S	**40**	0.000	–0.019	25	1.58%	5.66%	0.000	–0.005	40	2.34%	5.66%
S	**50**	0.000	0.045	29	1.78%	62.26%	0.000	0.041	49	2.76%	33.96%
V	**10**	–0.001	–0.145	10	0.72%	0.00%	–0.001	–0.092	10	0.74%	0.00%
V	**20**	–0.001	–0.238	19	1.13%	0.00%	–0.001	–0.199	19	1.14%	0.00%
V	**30**	–0.002	–0.426	26	1.48%	0.00%	–0.002	–0.335	29	1.61%	0.00%
V	**40**	–0.002	–0.324	33	1.84%	0.00%	–0.001	–0.262	39	2.13%	0.00%
V	**50**	–0.001	–0.219	36	1.99%	0.00%	–0.001	–0.230	49	2.63%	0.00%
G	**10**	0.000	0.064	8	0.54%	24.53%	0.000	0.044	10	0.64%	20.75%
G	**20**	0.002	0.309	16	0.91%	71.70%	0.001	0.214	19	1.06%	32.08%
G	**30**	0.001	0.164	21	1.16%	45.28%	0.001	0.157	29	1.56%	37.74%
G	**40**	0.001	0.103	26	1.41%	18.87%	0.001	0.144	39	2.06%	18.87%
G	**50**	–0.001	–0.109	35	1.86%	0.00%	0.000	–0.055	50	2.62%	0.00%
BH	**10**	0.000	0.026	10	0.74%	15.09%	0.000	0.014	10	0.72%	9.43%
BH	**20**	0.000	–0.058	19	1.14%	0.00%	0.000	–0.021	20	1.21%	0.00%
BH	**30**	–0.001	–0.157	24	1.37%	0.00%	–0.001	–0.116	29	1.61%	0.00%
BH	**40**	–0.001	–0.140	27	1.52%	0.00%	–0.001	–0.162	40	2.17%	0.00%
BH	**50**	–0.001	–0.118	34	1.89%	0.00%	–0.001	–0.162	49	2.63%	0.00%
BM	**10**	0.000	–0.064	10	0.65%	3.77%	–0.001	–0.168	9	0.61%	3.77%
BM	**20**	–0.002	–0.211	19	1.08%	5.66%	–0.002	–0.218	20	1.14%	5.66%
BM	**30**	–0.003	–0.383	28	1.54%	0.00%	–0.003	–0.379	29	1.59%	0.00%
BM	**40**	–0.003	–0.348	33	1.80%	0.00%	–0.003	–0.412	39	2.11%	0.00%
BM	**50**	–0.003	–0.461	39	2.11%	0.00%	–0.003	–0.462	49	2.62%	0.00%
BL	**10**	0.001	0.173	8	0.52%	90.57%	0.002	0.315	10	0.61%	98.11%
BL	**20**	0.001	0.071	16	0.90%	32.08%	0.001	0.134	19	1.05%	45.28%
BL	**30**	0.000	0.026	23	1.26%	20.75%	0.000	0.038	29	1.55%	20.75%
BL	**40**	0.000	0.046	28	1.51%	24.53%	0.001	0.075	39	2.06%	30.19%
BL	**50**	0.000	0.034	33	1.76%	1.89%	0.000	–0.019	49	2.57%	0.00%
SH	**10**	–0.002	–0.146	8	0.66%	0.00%	–0.001	–0.137	9	0.70%	1.89%
SH	**20**	–0.001	–0.115	16	1.06%	0.00%	–0.001	–0.125	19	1.20%	0.00%
SH	**30**	–0.002	–0.156	20	1.28%	0.00%	–0.002	–0.157	29	1.71%	0.00%
SH	**40**	–0.001	–0.100	24	1.53%	3.77%	–0.001	–0.114	39	2.23%	0.00%
SH	**50**	0.000	–0.030	26	1.62%	11.32%	0.000	–0.053	49	2.73%	0.00%
SM	**10**	–0.001	–0.096	9	0.68%	32.08%	–0.002	–0.164	10	0.76%	9.43%
SM	**20**	0.001	0.093	18	1.17%	39.62%	0.001	0.075	19	1.20%	49.06%
SM	**30**	0.001	0.176	26	1.55%	79.25%	0.001	0.191	29	1.69%	56.60%
SM	**40**	0.000	0.040	30	1.72%	11.32%	0.000	–0.009	40	2.21%	9.43%
SM	**50**	0.000	–0.017	33	1.85%	30.19%	–0.001	–0.075	49	2.65%	3.77%
SL	**10**	0.000	–0.055	8	0.54%	0.00%	0.000	–0.032	10	0.64%	5.66%
SL	**20**	0.000	0.015	16	0.94%	41.51%	0.000	0.007	19	1.08%	7.55%
SL	**30**	0.000	0.003	25	1.39%	0.00%	0.001	0.086	29	1.58%	9.43%
SL	**40**	–0.001	–0.081	25	1.38%	0.00%	0.000	–0.030	40	2.13%	1.89%
SL	**50**	–0.001	–0.122	32	1.74%	0.00%	–0.001	–0.070	49	2.58%	0.00%

Source: the authors.

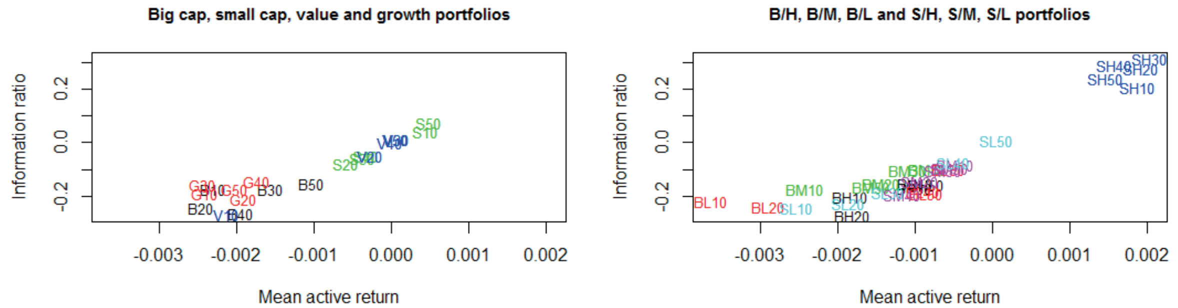
Appendix B



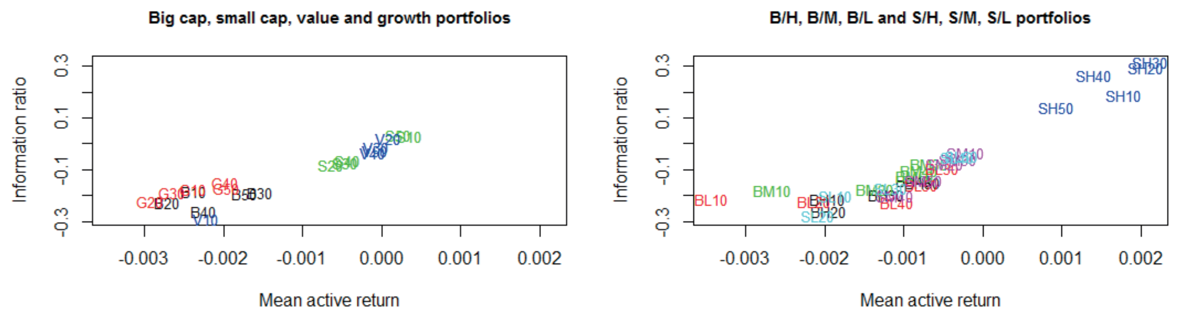
2a: *Performance positions of linearly tracked portfolios for Sample 1*
Source: the authors.



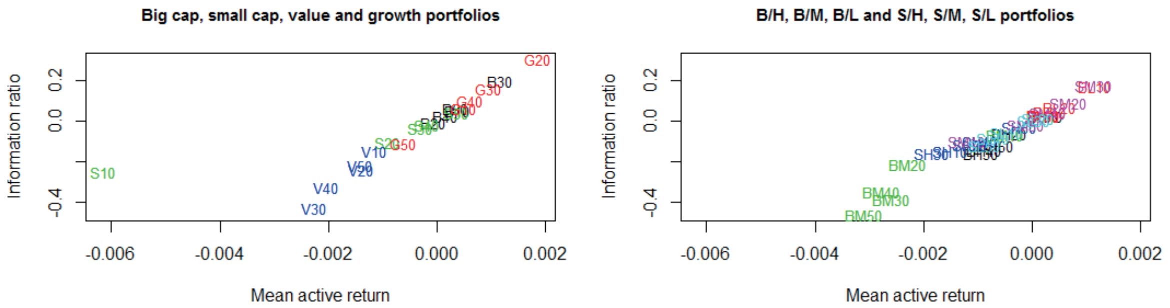
2b: *Performance positions of quadratically tracked portfolios for Sample 1*
Source: the authors.



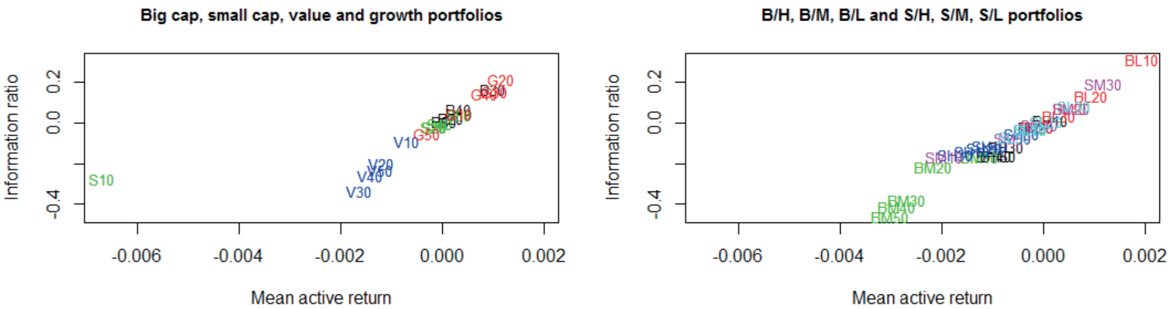
3a: *Performance positions of linearly tracked portfolios for Sample 2*
Source: the authors.



3b: *Performance positions of quadratically tracked portfolios for Sample 2*
Source: the authors.



4a: *Performance positions of linearly tracked portfolios for Sample 3*
Source: the authors.



4b: *Performance positions of quadratically tracked portfolios for Sample 3*
Source: the authors.

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