

## Research Insight

# Risk and Return of Factor Portfolios: *The Impact of Regression Weighting*

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## Introduction

Factor portfolios are long-short portfolios that have a unit exposure to a selected style factor and no exposure to all other styles. Such portfolios allow investors to surgically modify their investment portfolios to increase or hedge exposures. For example, portfolio managers may choose to tilt toward the Earnings Yield factor, aiming to capture a return premium, or they may choose to reduce exposure to the Beta factor in order to hedge market risk.

Unfortunately, factor portfolios are difficult to perfectly replicate since they contain long and short positions in all the assets of the estimation universe. In particular, many of the small-cap stocks may be expensive to trade and short. Another complication is that such factor portfolios may exhibit high turnover. Further, factor portfolios are not unique as the number of assets in the estimation universe greatly exceeds the number of factors in the model.

The asset weights in the factor portfolios will depend on the regression weighting scheme used to construct the factor portfolios. In this Research Insight, we examine the risk and return characteristics of the Barra US Equity Model (USE4) style factor portfolios under several regression weighting schemes.

# Construction of Factor Portfolios

As described by Menchero (2010), factor portfolios are constructed by performing a cross-sectional regression of stock returns against the factor exposures. The resulting stock weights therefore depend on the regression weighting scheme. In this Research Insight, we examine the USE4 style factors under four different types of regression weighting:

- Market capitalization weight
- Square root of market capitalization weight, also known as root-cap weight
- Ordinary least squares, referred to as equal weight
- Inverse specific variance weight

The econometric motivation for using inverse specific variance weighting is that it minimizes the sampling error in the estimate of the factor return. From a financial perspective, inverse specific variance weighting is important because it minimizes the predicted volatility of the factor portfolios. In practice, root-cap weighting is often used as a proxy for inverse specific variance.

For simplicity, throughout this paper, we will refer to the resulting portfolios by the name of the regression weighting scheme. It is important to note, however, that a factor portfolio resulting, for example, from an equal-weighted regression is not an equal-weighted portfolio. Nonetheless, we will see later that the weighting scheme is related to which stocks dominate the factor portfolio. An equal-weighted regression places more weight on small-cap stocks, so it is natural to expect that in the resulting factor portfolio, small-cap stocks would play a more important role. This does not imply that the factor portfolio has a small-cap tilt, since the small-cap stocks have larger weights on both the long and the short side of the portfolio.

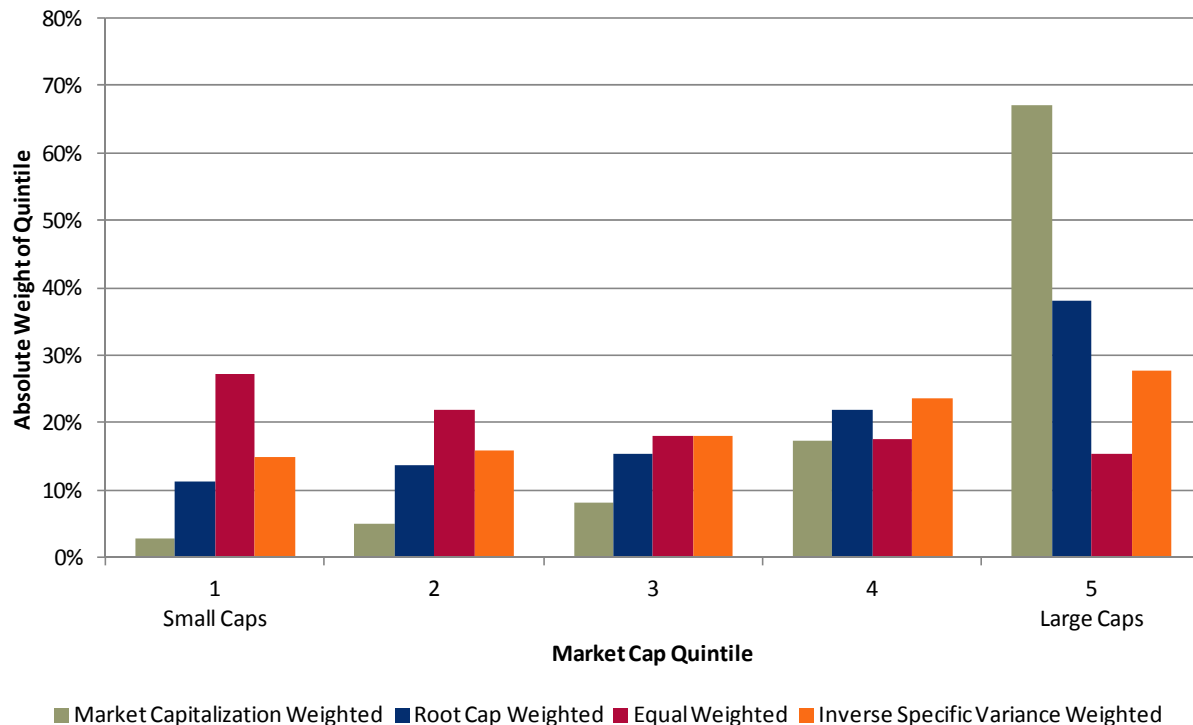
## Differences Due To Weighting

In this section, we investigate the impact of regression weighting on the factor portfolios. One difference lies in the relative weight of large and small-cap stocks in the factor portfolio. This is important for investors, because of the higher transaction costs typically associated with small-cap stocks.

To illustrate the relationship between regression weighting and the factor portfolio's stock size distribution, we divided the estimation universe stocks into five quintiles based on their market capitalization. Thus, the fifth quintile contains the largest stocks, while the first quintile contains the smallest ones. We then calculated the weight (using absolute values) of each quintile relative to the gross market value of the factor portfolios. In Figure 1, we report the results for the Earnings Yield factor. We repeated the calculation for each style factor, and found that the distribution of weights was qualitatively similar for all of them.

We can make several interesting observations. First, the weight distribution depends heavily on the regression weighting scheme. For market capitalization weighting, about two thirds of the portfolio weight is in the largest quintile. For equal weighting, by contrast, the five market-cap quintiles are roughly equally represented, with a slight tilt towards the smallest quintile. Not surprisingly, root-cap weighting leads to a distribution between market cap and equal weighting. Finally, we observe that inverse specific variance weighting leads to a distribution similar to root-cap weighting.

**Figure 1: Absolute (Long+Short) weight of market-cap quintiles for each regression method, Earnings Yield factor of the USE4 model, as of September 14, 2012.**



These observations have important implications for investors wanting to replicate factor portfolios. Since small-cap stocks are generally more illiquid and more costly to short, the implementation of an equal-weighted factor portfolio could prove more difficult and costly than the implementation of the other three approaches.

Next, we compare the long-run risk-adjusted performance of four versions of style factor portfolios. We selected the Momentum and the Earnings Yield factors to illustrate the performance differences associated with different factor portfolio weightings. Both factors represent popular investment strategies, and have performed well since 1995, as seen in Table 1.

In Figure 2, we present the long-run performance of the Earnings Yield factor portfolios. Over the sample period, we see that the regression weighting had a relatively minor impact on factor performance. The possible exception is for market-cap weighting, which slightly underperformed the other three. Note that all four factor portfolios exhibit the same characteristic behavior of the Earnings Yield factor; for example, an underperformance in the late 1990s during the run-up phase of the dot-com bubble, which was followed by a sharp rebound after the bubble burst in 2000.

Figure 2: Performance of Earnings Yield Factor Portfolios, USE4 Model, July 1995 – September 2012.

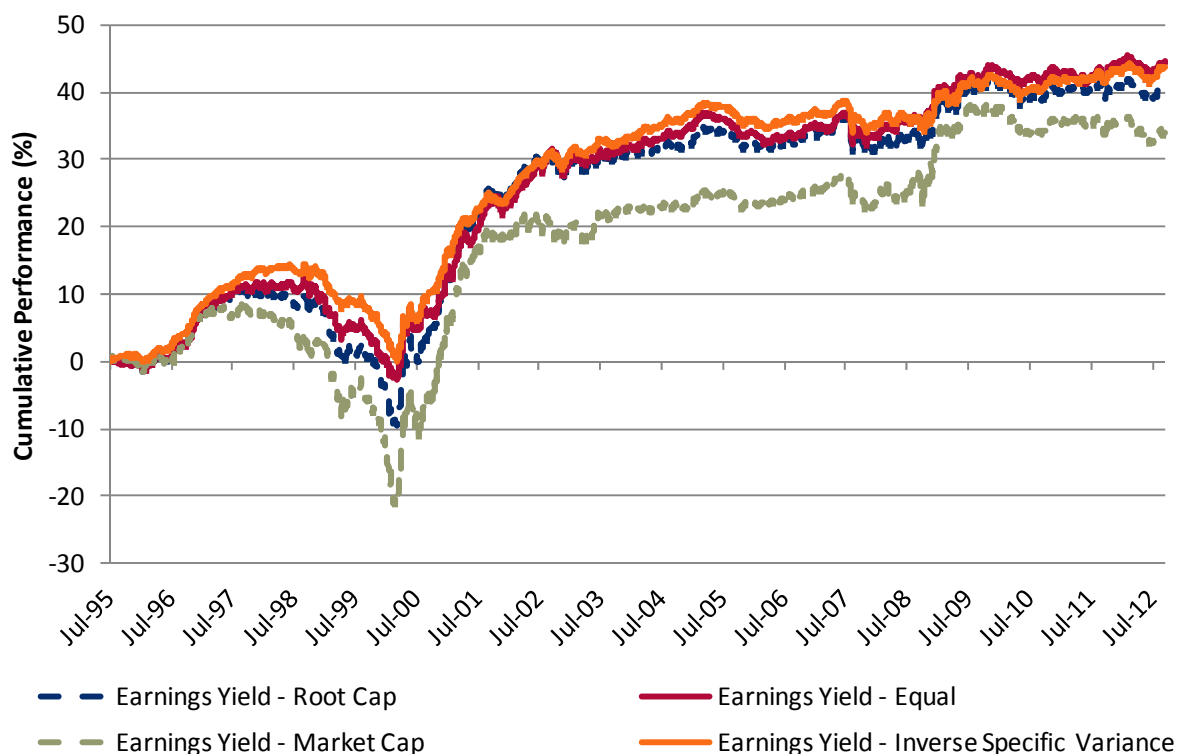
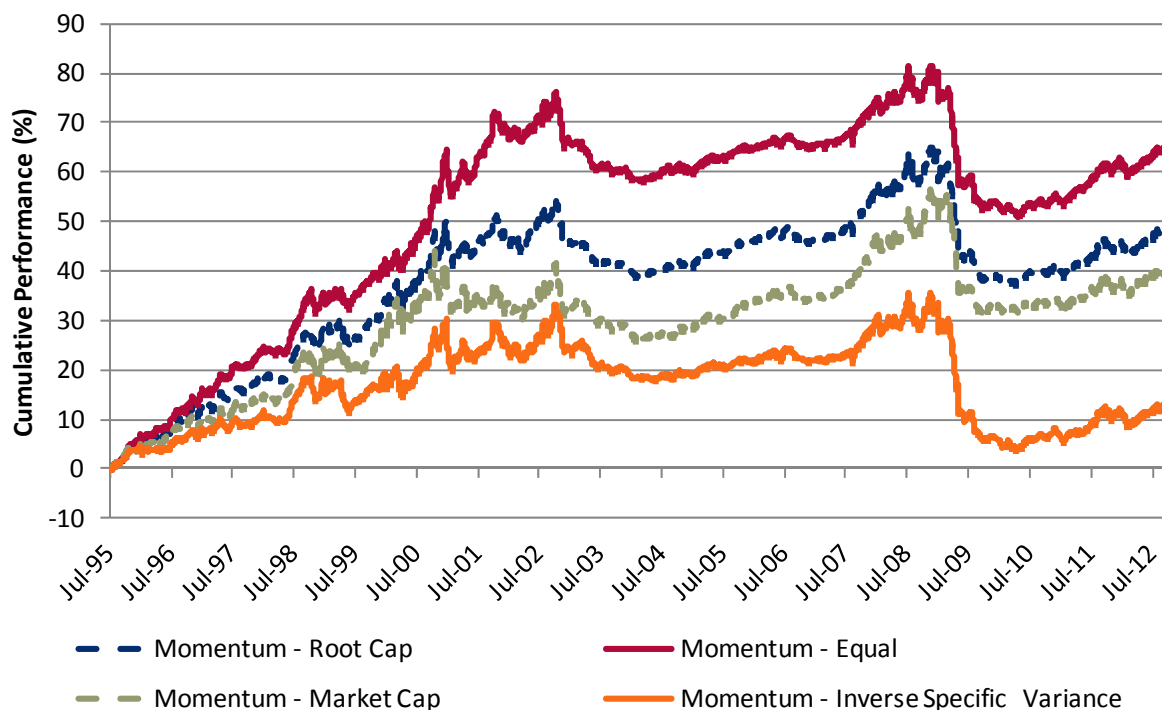


Figure 3: Performance of Momentum Factor Portfolios, USE4 Model, July 1995 – September 2012.



In Figure 3, we show the cumulative performance of the four Momentum factor portfolios. Here, the regression weighting scheme led to much greater differentiation in factor performance. The top-performing Momentum factor was for equal weighting, which outperformed root-cap weighting, which in turn outperformed market-cap weighting. The worst performing Momentum factor was for inverse specific variance weighting, which underperformed the others substantially. Finally, note that all four portfolios exhibit the same characteristic crashes of Momentum in 2002 and 2009.

In Table 1, we report summary statistics on performance and realized volatility for all USE4 style factor portfolios. In terms of performance, regression weighting can have a significant impact for some factors. For instance, for the Momentum factor the maximum performance difference exceeded more than 300 bps. For most factors, however, the impact of regression weighting was more modest; typically the maximum performance difference was below 100 bps.

In terms of realized risk, Table 1 shows that the inverse specific variance weighted portfolios had the lowest realized risk for every factor. This is consistent with the interpretation that such portfolios have the minimum risk with unit exposure to the factor (and zero exposure to all other factors). Interestingly, the cap-weighted factor portfolios had the highest volatility for virtually all factors. This is likely due to the fact that cap-weighted factor portfolios tend to be more concentrated than the factor portfolios from other regression-weighting schemes.

Table 1: Summary statistics for USE4 style factor portfolios, July 1995 to September 2012.

Factor	Return (annual, %)				Volatility (annual, %)				Information Ratio			
	Market Cap	Root Cap	Equal	Inverse Specific Variance	Market Cap	Root Cap	Equal	Inverse Specific Variance	Market Cap	Root Cap	Equal	Inverse Specific Variance
Beta	-0.76	-0.64	-0.17	-0.14	9.15	8.70	8.62	8.60	-0.08	-0.07	-0.02	-0.02
Non-linear Beta	-0.14	0.02	0.46	-0.03	2.73	2.09	2.04	1.83	-0.05	0.01	0.23	-0.01
Book-to-price	-0.48	0.08	0.53	-0.26	3.09	2.00	2.07	1.56	-0.16	0.04	0.26	-0.16
Dividend Yield	1.46	0.81	1.06	0.68	2.90	1.95	1.79	1.47	0.50	0.42	0.59	0.46
Earnings Yield	1.96	2.37	2.58	2.54	3.97	2.76	2.57	2.09	0.49	0.86	1.01	1.21
Growth	0.53	0.09	-0.32	0.36	3.01	2.06	1.96	1.55	0.18	0.04	-0.16	0.23
Leverage	-0.84	-0.50	-0.47	-0.89	2.75	1.93	1.96	1.54	-0.31	-0.26	-0.24	-0.58
Liquidity	2.03	1.57	1.82	1.55	3.41	2.62	3.10	2.25	0.60	0.60	0.59	0.69
Momentum	2.24	2.73	3.70	0.66	5.08	4.18	3.95	3.82	0.44	0.65	0.93	0.17
Residual Volatility	-3.49	-3.28	-2.95	-1.77	4.91	3.91	3.80	3.32	-0.71	-0.84	-0.77	-0.53
Size	-3.74	-3.67	-4.36	-3.03	3.49	3.26	3.58	3.21	-1.07	-1.13	-1.22	-0.94
Non-linear Size	-1.23	-1.62	-2.68	-1.57	4.24	3.14	3.04	2.78	-0.29	-0.52	-0.88	-0.57

In Table 2, we report the time-series (return) correlation coefficient of the four style factor portfolios for each of the factors. Among factors, the highest correlations were generally for Beta, Momentum, Residual Volatility, and Size. These factors also tended to have the highest volatilities, as shown in Table 1. As for different regression-weighting schemes, the correlations tended to be quite high (generally above 0.80). The exceptions were for market-cap weighting versus equal weighting or inverse specific variance weighting; in these cases the average return correlations were 0.60 and 0.70, respectively.

**Table 2: Time-series (return) correlation of the four families of factor portfolios, USE4 Model, July 1995 to September 2012.**

Series 1	Series 2	Beta	Non-linear beta	Book-to-price	Dividend Yield	Earnings Yield	Growth	Leverage	Liquidity	Momentum	Residual Volatility	Size	Non-linear Size	Average
Market Cap	Root Cap	0.97	0.87	0.83	0.86	0.85	0.84	0.85	0.79	0.91	0.89	0.95	0.88	0.87
Market Cap	Equal	0.90	0.56	0.43	0.52	0.53	0.48	0.49	0.46	0.74	0.67	0.85	0.55	0.60
Market Cap	Spec Var	0.93	0.67	0.62	0.62	0.68	0.62	0.65	0.51	0.81	0.76	0.85	0.70	0.70
Root Cap	Equal	0.98	0.85	0.79	0.82	0.85	0.81	0.82	0.87	0.93	0.90	0.94	0.85	0.87
Root Cap	Spec Var	0.98	0.89	0.87	0.86	0.89	0.85	0.89	0.86	0.94	0.92	0.94	0.90	0.90
Equal	Spec Var	0.98	0.88	0.78	0.85	0.83	0.81	0.83	0.87	0.92	0.89	0.94	0.85	0.87
Average		0.96	0.79	0.72	0.75	0.77	0.74	0.75	0.73	0.88	0.84	0.91	0.79	

## Conclusion

Factor portfolios have a unit exposure to a risk model's selected factor and zero to every other factor. They can be used as investment strategies to capture return premia, or as hedges of factor risk. In this Research Insight, we focused on four systematic ways of their construction using different regression weighting schemes.

The weighting scheme chosen determines which stocks dominate the factor portfolio. We found that small-cap stocks played the most important role in equal-weighted portfolios, while large-cap stocks dominated in market cap weighted portfolios. Given the generally higher transaction costs of small-cap stocks, this implies equal-weighted factor portfolios are more costly to implement.

We also investigated the risk and return characteristics of factor portfolios. In some cases (e.g., Momentum), the return differences between different regression-weighting schemes could be quite large. For most factors, however, such return differences were relatively minor. In terms of risk, we found that inverse specific variance weighting led to the lowest volatilities, whereas market-cap weighting generally led to the highest volatilities.

Finally, we examined the return correlations between the factor portfolios under different regression-weighting schemes. We found that these correlations were generally quite high, especially between root-cap weighting and inverse specific variance weighting. The correlations also tended to be higher for more volatile factors, such as Beta.

## References

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