QRAFT

New Model of AI Driven Asset Management
Higher Alpha with Lower Cost through AI Technologies

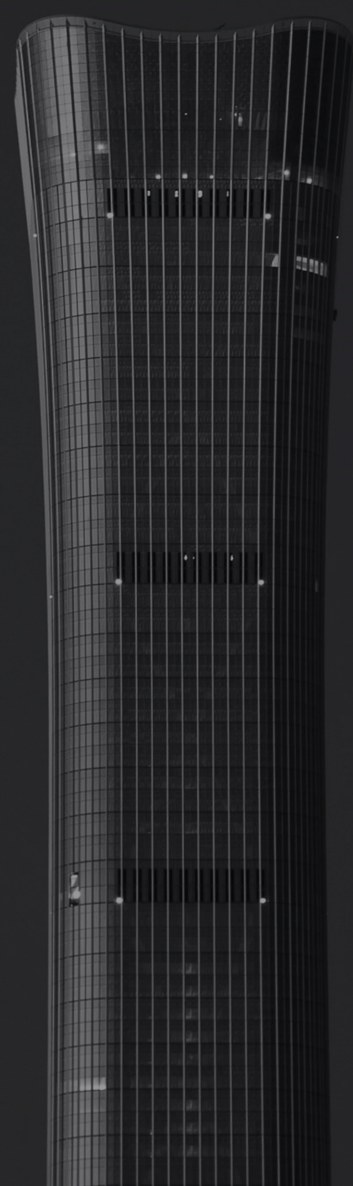
QRAFT AI Quant Series

Factor Tilting Portfolios

Which is superior Tilting methodology?

Senior Manager, Eunchong Kim
Manager, Hanwook Jeong
Manager, Myongseok Chae

September
2020



Contents

QRAFT Technologies
+82 2 487 8555
qraft@qraftec.com

[**Home page**] https://www.qraftec.com/
[**Subscribe to Newsletter**] https://www.qraftec.com/newsletter

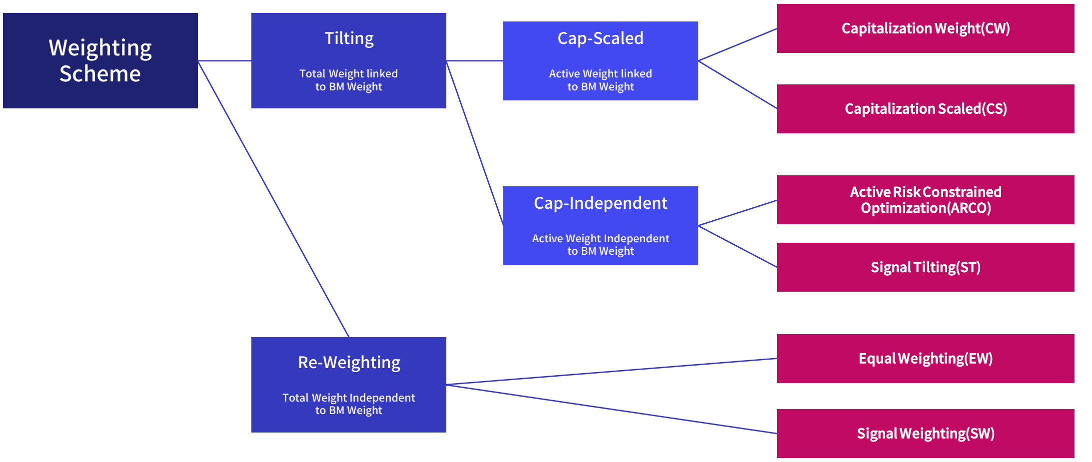
Summary

Factor Tilting refers to a method of exposing a portion of a portfolio to a factor investing strategy. The quantitative factor calculation utilizes all the observable data such as stock prices, financial data, and forecasts for the company. This research performs and compares different factor tilting through several methodologies. How much a portfolio is exposed to a factor and how it will have effect is different according to different tilting methodology.

Prior to applying the factor tilting methodology, the robustness of well-known factors was checked. We continued the research using momentum factor, since performance trend was more pronounced as we divide stocks into more quantiles. For detailed evaluation of various tilting methodologies based on the momentum factor, we compare different strategies by examining excess returns, factor exposure, and turnover of each. All investigated tilting methodologies show positive IR values when studying its excess returns for the entire period, proving their advantage over pure passive investment. Among those, the signal tilting (ST) method was the most dominant with an IR of 0.1394, and the Capitalization Weight (CW) method shows the lowest at 0.0584. When looking at the factor exposure, all tilting methodologies showed positive and significant active factor exposure. Both signal weighting (SW) and signal tilting (ST) have the largest in terms of active exposure, while active risk constrained optimization (ARCO) and capitalization weight (CW) appears to have relatively low exposure. With turnover of a portfolio, capitalization weight (CW) was the lowest, and the signal tilting (ST) method showed the highest turnover.

We expect the result and the analysis of each method to help investors understand the characteristics and performance of each tilting method and help implement appropriate tilting methodologies. As mentioned above, various tilting methodologies can be used for various factors, and when multiple factors are used, a more diverse portfolio can be formulated. The analysis also shows that tilting methods provide better risk-adjusted return compared to the benchmark, so that higher performance can be pursued with the same level of risk. Recently, many global asset managers are releasing smart beta ETFs tailored to new themes and management philosophy of each manager. The trend suggests that it may be necessary to pay more attention to the tilting strategy.

[Main Diagram] Weighting Scheme



Source: Equity Smart Beta and Factor Investing for Practitioners, 2019

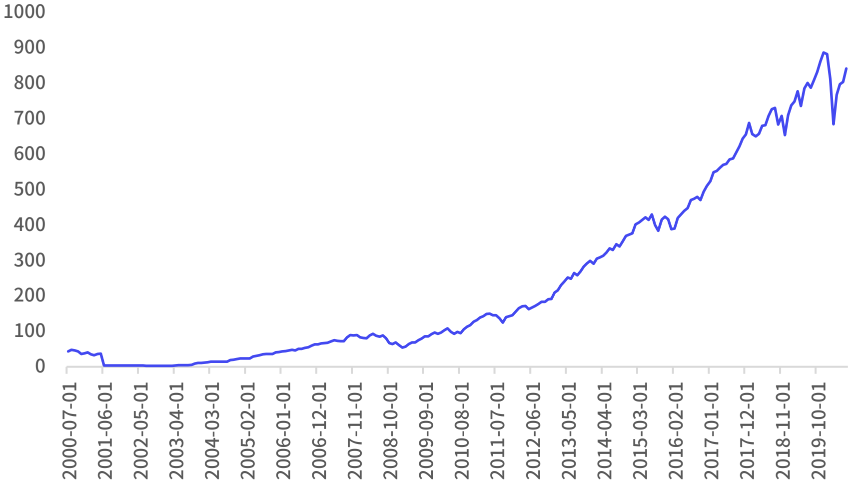
Introduction

Various research papers and analysis reports on smart beta strategies are being published, but among them, this report focuses on the factor tilting strategy. A factor tilting refers to a strategy that pursues higher returns compared to the benchmark by adjusting the proportion of investment in the passive weighs. The investment weight may be assigned higher or lower compared to benchmark weight by conducting quantitative analysis.

Factor tilting refers to a method of exposing a portion of a portfolio to an equity factor strategy. Equity factor refers to a factor that can explain the difference in returns among stocks, and research on the equity factor is continually being conducted in academia. Equity factors such as size, value, asset growth, leverage, term structure, and carry are well-known (Swedroe and Larry, 2016), and the factor value calculation uses observable data ranging from stock price, financial data of each company, and to forecasts of the companies' future. Then, the weight of each stocks is determined following the benchmark portfolio and adjusted by assigning a larger or a lower weight based on the calculated factor value. Hubert Dichtl et al (2018) researched factor tilting using different factors such as valuation, spread, momentum, and volatility. The research found that tilting using the relative strength of each factor created diversification effect and improved the risk-adjusted return compared to the benchmark, while limiting the maximum drawdown of the portfolio. The finding suggests that investors can pursue the excess risk-adjusted returns using factor tilting rather than following simple benchmarks.

It is also necessary to pay attention to the recent trend of increasing investment using the smart beta strategy to appreciate the value of factor tilting. The smart beta strategy belongs to a larger category of factor tilting strategies, and its methodology is also becoming more diverse. [Figure 1] shows the total market capital of Smart-Beta ETFs, which shows significant increase since 2009.

[Figure 1] Total Market Capital of Smart-Beta ETFs[3]

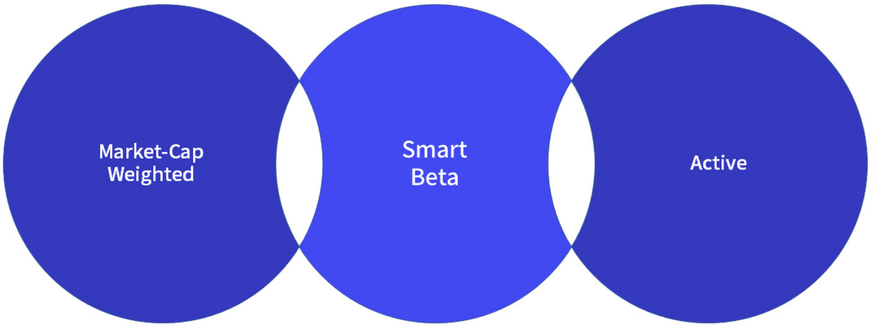


Source: QRAFT Technologies, Compustat
Unit: Billion

[1] Andrew L. Berkin & Larry E.Swedroe, 2016, Your Complete Guide to Factor-based Investment, A BAM ALLIANCE BOOK
[2] Hubert Dichtl, Wolfgang Drobetz, Herald Lohre, Carsten Rother and Patrick Vosskamp, 2019, Optimal Timing and Tilting of Equity Factors, Financial Analysts Journal, 75-4, 84-102
[3] Market capital calculated using 652 Smart-Beta ETFs obtained from DataStream. Approximate number of smart-beta ETFs estimated at 900.

Smart beta strategies expand the uses of equity factors discovered by past researches and provides higher risk-adjusted return. Most passive investments duplicate indices based on market-cap weights; hence, most passive investment is conducted using market-cap weights for portfolio composition, and the well-known factor effect cannot be implemented.

[Figure 2] Diagram of Smart Beta



Source: QRAFT Technologies

[Figure 2] describes the diagram of smart beta strategy. The smart beta strategy refers to a portfolio that adds a factor tilting of the active investment method to the passive investment that follows the benchmark. Passive investments have advantage in low transaction costs, low turnover, and abundant liquidity. However, one cannot expect a return beyond the market benchmark. On the other hand, active investment pursues higher returns compared to the market with higher risks. Factor tilting allows you to pursue both the passive strength and the active strength. In addition, factor tilting induces exposure to well-known factors, rather than focusing on the investment styles of sectors, countries, and individuals. It is also possible to construct a portfolio that considers the risk appetite of investors depending on which factors to have exposure.

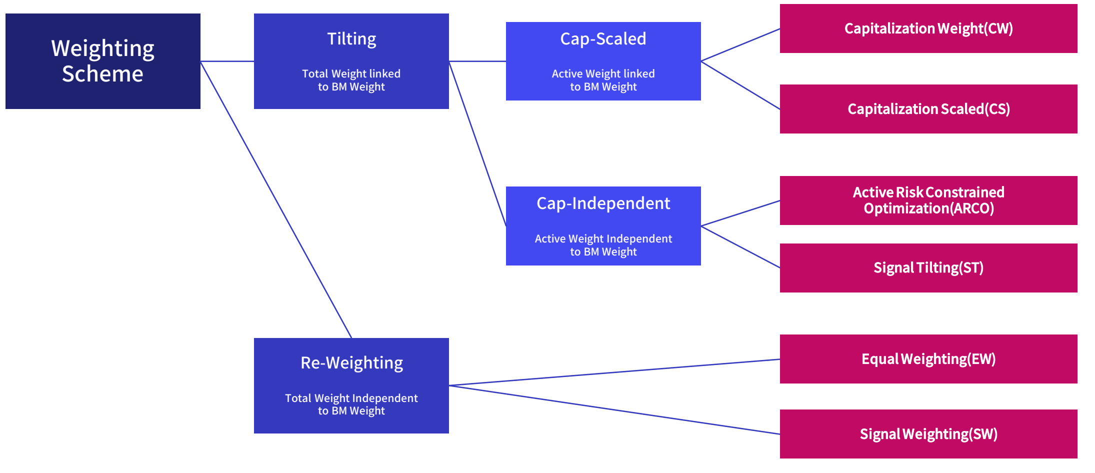
It is important to determine how much exposure the portfolio needs to have in factor tilting. There are largely two methods. One is to select the top N stocks based on a specific factor value, while mainly following the benchmark weights. By choosing simply N stocks, investors can expect to have the factor effect intact. In other words, we can maintain the factor exposure as intended by combining the top N equal-weight portfolio with benchmark portfolio at predetermined ratio. However, in this case, small-cap stocks may occupy an excessively high proportion, incurring high transaction costs from slippage, low liquidity, and high turnover.

Another way to construct a portfolio is to adjust the overall benchmark weight to a corresponding factor. If the factor weighting is adjusted generally relative to the benchmark, companies with high market capitalization and high factor values will have more weights. In other words, higher the market cap stocks will affect more to the factor exposure. In this case, the problem with small-cap stocks as mentioned above can be remedied to some extent. However, when a stock with a low factor value has a high market capitalization the factor exposure intended will be largely decreased, reducing the effectiveness of the factor tilting strategy.

In conclusion, the performance of factor tilting depends on how well the two methods mentioned above are combined. It will dictate how much the exposure investors will have to that factor. This research investigates several tilting methodologies. The result compares how much the portfolio is exposed to a certain factor and how effects are different among several methodologies thus providing justification for overall tilting strategy. In addition, we examine which of those methodologies are superior through detailed performance analysis.

Weighting Scheme

[Figure 3] Weighting Scheme



Source: Equity Smart Beta and Factor Investing for Practitioners, 2019 [4]

[Figure 3] shows the weighting scheme of smart beta. Currently, most smart beta strategies adjust the weight of the benchmark (BM) to keep factor exposure and tracking error within range or assign a new weight according to the calculated factor value to maximize factor exposure. The weight adjustment corresponds to tilting in the above [Figure 3] and the new assignment corresponds to Reweighting. Factor tilting in this research encapsulates all the methodologies that increase the specific factor exposure, and is a term that includes Tilting and Reweighting, which are main branches of the weighting scheme.

$$Portfolio\ Weight = Active\ Weight + Bench\ Mark\ Weight$$

For understanding, we explain classification of Tilting methodologies from above equation. First of all, The total weight of the portfolio is composed of active weight + BM weight. It means that the weight of the final portfolio is the sum of BM weight and active weight that is adjusted from BM weight to create factor exposure.

When the adjustments of each stock weight are not made at all (Active Weight = 0), it becomes the BM weight. On the other hand, if BM Weight is not considered at all in portfolio composition (BM Weight = 0), only Active Weight remains, and this case is called re-weight method in [Figure 3].

Tilting method refers to, however, the case where both Active Weight and BM Weight are included in the portfolio. It means specific stocks receive over or under weighting compared to BM weight, thus sharing a certain portion of the benchmark portfolio. The tilting is further classified into Cap-scaled and Cap-independent. In Cap-scaled system, the active weight is expressed as a function of BM, while in Cap-independent decided separately from the BM. In order to understand this in detail, we study four tilting methodologies and two reweighting methodologies.

[4] Khalid Ghayur, Ronan G.Heaney and Stephen C. Platt, 2019, Equity Smart Beta and Factor Investing for Practitioners, Wiley

1. Cap-Scaled: Capitalization-Weighted

Capitalization-Weighted (CW) is a sub-category of cap-scaled methodology, which starts from selecting stocks within the BM universe. All stocks in the BM are ranked according to the factor score, and cumulative coverage is provided according to the ranking. Here, the coverage is defined by how much BM weighting in the tilting portfolio will be assigned.

[Table 1] CW Example

	Stock Momentum (Total Return)	Benchmark Weight(%)	Cumulative Coverage of Benchmark Weight(%)	Total Weight in Momentum Portfolio(%)	Active Weight in Momentum Portfolio(%)
Stock1	90.20	0.50	0.50	1.00	0.50
Stock2	85.40	1.00	1.50	2.00	1.00
Stock3…	82.50	0.50	2.00	1.00	0.50
…	…	…	…	…	…
…Stock n…	8.20	3.00	50.00	6.00	3.00
Stock n+1…	7.50	0.75			

Source: Equity Smart Beta and Factor Investing for Practitioners, 2019

[Table 1] shows an example of the CW method with cumulative coverage ratio of 50%. After sorting the stocks in the BM in descending order according to the factor score, the weight of the stocks in the BM is cumulatively added. When the cumulative sum reaches 50%, only the stocks that are selected to this level (stock n in the figure) are added to the portfolio. After selecting stocks up to the selected stock n, we assign final portfolio weight based on selected stocks' market capital.

$$Portfolio\ Weight_i = \left(\frac{Cap_i}{\Sigma(Cap_i)}\right) * \left(\frac{1}{p}\right) = CapW_i * (1\ /\ p)$$

$$Active\ Weight_i = Portfolio\ Weight_i - \ CapW_i = CapW_i * ((1\ /\ p) - 1)$$

$$Cap_i\text{: Market Capital of Stock } i$$

$$\Sigma Cap_i \text{ : Total Market Capital of Selected Stocks}$$

$$p\text{: BM Cummulative Coverate Ratio}$$

$$CapW_i\text{: Stock } i'\text{s Weight within the BM}$$

To express this mathematically, the final weight of the selected stock i is the reciprocal of stock i's benchmark weight × cumulative coverage ratio. Active weight becomes the difference between BM weight and Portfolio Weight. From the above example, since the coverage ratio is 50%, the final weight is 2 times the market cap weight (=1 / 0.5) up to the stock n. In other words, in the CW method, the coverage ratio acts as a parameter that determines each stock's weight of the tilting portfolio.

The mentioned method has difference in selection process of stocks even though it is similar to the generally known top N selection strategy. When number of stocks are determined, the selected stocks based on the factor signal may cause excessive tracking error due to changes in weights within the portfolio compared to BM weight. The CW method, however, has pre-determined coverage ratio first and then the number of stocks to be included will be fixed. This process ensures consistency of weights relative to market capital, providing reduced tracking error. In this research following equally weighted portfolio uses the CW method.

2. Cap-Scaled: Capitalization-Scaled

The second cap-scaled method, Capitalization-Scaled(hereinafter CS), determines portfolio weights by selecting either top stocks based on the factor score, or includes all the stocks within the BM, multiplying the factor score to the weight and then rescaling the whole portfolio. The process ensures that the stock with high factor score receives larger weight when constructing a portfolio.

$$Portfolio\ Weight_i = CapW_i * S_{i,j}$$

$$\text{Active } Weight_i = Portfolio\ \ Weight_i - CapW_i = CapW_i * \left(1 - \ S_{i,j}\right)$$

$CapW_i$: Stock i's Market Cap Weight in the BM, $S_{i,j}$: $Factor$ Score of Stock i calculated on Factor j

As in the above equation, the Portfolio Weight is determined by multiplying the market capitalization in the BM of the individual stock by the factor score. Active weight can be calculated as the difference between Portfolio Weight and Market Capitalization. Like CS, CS reflect the features of Cap-Scaled. Since the Portfolio Weight of stock i is composed of "Factor Score × BM Weight", the active weight is expressed as "BM Weight × (Factor Score – 1)". And this form implies that the Active Weight is determined by the BM Weight.

In the case of Factor Tilting, a Long-Only Portfolio is formed, but we could not simply use the Factor's Z-score. Sine the Z-score value has both negative and positive numbers, it needs to be adjusted. There are several ways to calculate the Factor Score, but in this paper, the value of each factor is calculated as follows after taking Z-score.

$$Factor\ Score = \begin{cases} (1+Z), & Z > 0 \\ (1-Z)^{-1}, & Z < 0 \end{cases}$$

All of the calculated Factor Score have positive values, and if the Z-score is greater than 0, a value greater than 1 is assigned, and if it is a negative number, it has a value between 0 and 1. Therefore, stocks with a high Factor Score receive a greater weight compared to the existing benchmarks when constructing a factor portfolio, and stocks wi a low Factor Score receive a lower weight compared to the BM.

MSCI Tilt index is an example of CS weighted index, and there are indices incorporating momentum, quality, size and volatility. Each index assigns score to each stock with pre-defined factor, and the final index is calculated by multiplying scores with stock's market capital weight.

3. Cap-Independent: Active Risk Constrained Optimization

Active Risk Constrained Optimization(hereinafter ARCO) method proceeds tilting under given constraints such as tracking error or turnover that asset managers can permit. With the constraints given by the asset manager, ARCO maximizes or minimizes the objective function, which is usually maximizing Factor Score × Weight, to obtain optimal weights. Domestic indices such as KOSPI 200 / Quality / Value / Volatility tilt are the examples facilitating ARCO, and the actual objective function and weight constraints are as follows

$$\begin{aligned} &Maximize\ \Sigma S_i w_i \\ &subject\ to\ \ 1.\ \ 0\% \le w_i \le 30\% \\ &2.\ \ |w_i - k_i| \le 0.5\% \\ &3.\ \ w_i \le 3 \times k_i \\ &4.\ \ \Sigma w_i = 100\% \end{aligned}$$

The portfolio weight is determined by optimizing above constraints and objective function. Constraints shows the characteristics of ARCO well, which preserves BM weights as much as possible due to the constraints set to limit the difference between the optimized and BM weight. The active weight, therefore, is simply the difference between the Optimal Weight and the BM weight. This weight is the result of the optimization process, which may not be related to the BM weight, thus can be classified as Capital-independent weights.

Since the constraints and parameters does not have to be restricted to the example given above, investors can obtain diverse range of portfolios. Other constraints such as turnover of the portfolio and exposure to various factors can be implemented according to requirements asset managers need to meet. The parameters and constraints may hinder the optimization process, thus choosing appropriate settings of the algorithm may be important skills for the asset manager.

4. Cap-Independent: Signal Tilting

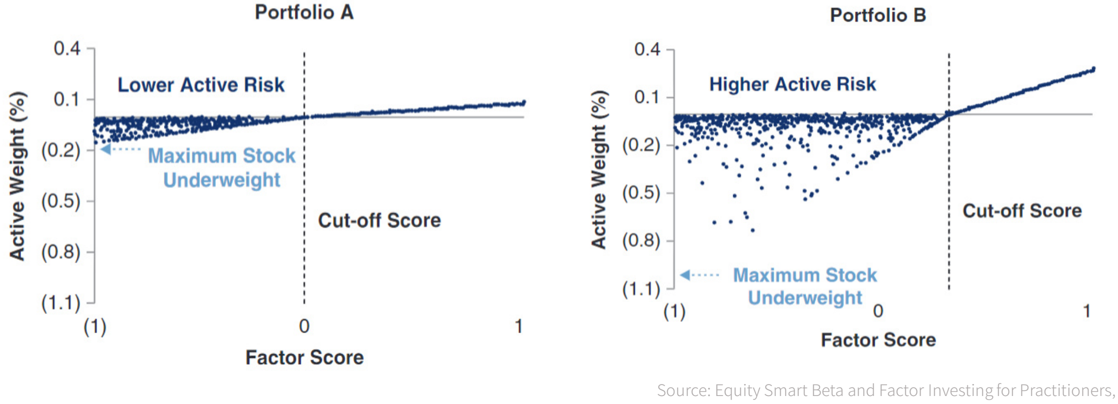
Signal Tilting(hereinafter ST) method transfers the weight from stocks with low factor score to ones with high factor score. The method utilizes two parameters, namely, cut-off score and MaxUW(Maximum under-weight). Cut-off score determines the level of factor score to be either high or low, while MaxUW dictates how much weight should be transferred from low-score stocks to high-score stocks.

$$UnderWgt_i = Max(S_i * MaxUW, -CapW_i)$$
$$OverWgt_i = (\frac{S_i}{\Sigma S_i} * \Sigma UnderWgt_i)$$

$$Portfolio\ Weight_i = \begin{cases} CapW_i - UnderWgt_i, & \text{Cut} - \text{off Score} > \text{Factor Score} \\ CapW_i + OverWgt_i, & \text{Cut} - \text{off Score} < \text{Factor Score} \end{cases}$$

For example, if the MaxUW is set to -10% (should be always negative), the weights of low factor scores will be reduced by 10%, which will be added to the high factor score stocks' weights. One precaution is to select the minimum of stock i's benchmark weight and factor score * MaxUW since the weight cannot be negative (under the long-only constraint). Through this process, reduced weight from the low score stocks are allocated to high score stocks in proportion to their factor scores. Similar to ARCO, ST can be classified as cap-independent weighting scheme because the active weight is determined independent of benchmark weight by parameters such as MaxUW, and cut-off score.

[Figure 4] ST Portfolio Construction for Parameter



Source: Equity Smart Beta and Factor Investing for Practitioners, 2019

Signal tilting can utilize various levels of parameters, and [Figure 4] shows the tendency of active weights obtained from different parameters. Portfolio A is set with cut off score of 0 and MaxUW of 0.2, while portfolio B has cut off score > 0 and MaxUW > 0.8. In each portfolio, we can observe that variations of active weight for each stock are different. Although portfolio A contains more underweight targets from lower cut off score, the lower MaxUW parameter offsets the effect by transferring less weight from the targets. Portfolio B on the other hand, shows higher variation of active weights arising from higher MaxUW, which entails higher risk.

5. Reweighting: Equal Weighting(EW)

It is rather easy to compose EW portfolio, since the scheme involves selecting all or some of stocks based on factor score, then allocating equal weights to those. As mentioned in CW scheme, the parameters in the EW can be the number of stocks or the coverage ratio. This research adapts coverage ratio to maintain consistency of stock weights in the benchmark. Stock selection process follows that of CW method: After calculating and sorting factor score for each stock, we cumulatively add stock i's weight within the BM. When the cumulative sum reaches coverage ratio, selected stocks during the process is included in tilting portfolio, allocating equal weights in the portfolio.

EW method is classified as reweighting scheme since tilting portfolio weight is determined as equally irrespective of benchmark weights.

6. Reweighting: Signal Weighting

Weighting scheme using the strength of factor scores to distribute is referred to signal weighting (SW). While weighting in EW is determined by the number of stocks in the portfolio, SW distributes high weights to stocks with high factor score and low weights to low factor score, respectively. Since SW is independent of BM weights, its operability may vary according to the selected universe.

$$Portfolio\ Weight_i = \frac{S_{i,j}}{\left(\Sigma(S_{i,j})\right)}$$

$S_{i,j}$: *Factor Score of Stock i calculated by Factor j*

The Weight of the Tilting portfolio through SW is determined by the Factor Score. One thing to keep in mind is that using raw z-score does not return the weights for the portfolio, hence it is necessary to convert numbers to positive values. Tilting portfolio using SW is solely determined by the factor score, hence it is in line with EW as they both are under category of reweighting.

Empirical Anaylsis

In this section, we analyze a performance for each tilting methodology. At this time, the investment universe is follows, and the parameters that must be preceded by each methodology of Factor Tilting are applied as follows. Others not mentioned shall be used as described in each Factor Methodology.

- ✓ Universe: NYSE + NASDAQ Top 20% Market Cap
- ✓ Benchmark: Market Value-Weighted Portfolio of the stocks in the universe.
- ✓ Parameter

  CW: coverage ratio = 0.7

  EW: coverage ratio = 0.7

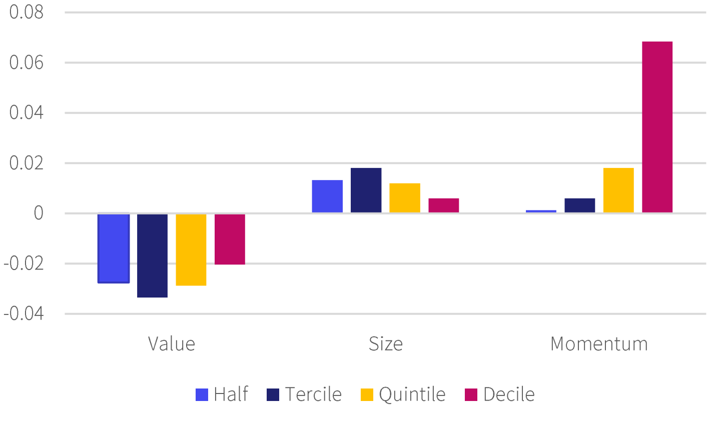
  ST: MaxUW = 0.5, Cut-off Score = 30% of the Factor Score

  ARCO: Weight Upper/Lower Limit = within ±10%, The absolute difference between the weight within the benchmark and the portfolio < 0.1%, Weight in Portfolio < Weight in Benchmark × 2

1. Factor Robustness Check

To select a factor for tilting, we first analyze the robustness of factor. It would be useful to investors to use the factor whose return has been producing significant alphas to apply the tilting to enhance the factor return. Size, momentum, and value has been selected as candidates which have been three of the most popular factors. We use the inverse of market cap, previous 12m-1m cumulative return, and the inverse of PBR to measure size, momentum, and value, respectively.

[Figure 5] Factor Long-Short Annual Return



Source: QRAFT Technologies, Compustat

[Figure 5] shows long-short return for each factor from Jan 2001 to Aug 2020. Each bar represents long-short return based on different numbers of quantiles used for factor calculation. Hence, if the factor is robust, we expect the long-short return to be larger as divide portfolios finer as it possesses larger exposure to the factor. The figure shows momentum is the only factor with this feature which concludes momentum is more robust than size and value.

We also compare monthly excess returns, CAPM(Sharpe, 1964)[5]'s alpha, and Fama-French (1993)[6] 3 factor model's alpha to test the robustness. We use Newey and West (1987)[7] standard errors where we allow 12 lags for the t-test.

[Table 2] Factor Robustness

This table computes long-short returns based on decile portfolios and shows monthly excess returns, CAPM(Sharpe, 1964)'s alpha and Fama-French (1993) 3 factor model's alpha. Newey and West (1987) standard errors in the parentheses where we allow 12 lags. The sample period is from Jan 2001 to Aug 2020.

	Excess return	CAPM Alpha	FF3F Alpha
Panel A: Value Weight			
Size	0.0003	0.0002	-0.0007
Value	-0.0038	-0.0049	-0.0039*
Momentum	0.0064	0.0094**	0.0090**
Panel B: Equal Weight			
Size	0.0005	0.0006	-0.0002
Value	-0.0033	-0.0039	-0.0027
Momentum	0.0053	0.0094*	0.0085*

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10
Source: QRAFT Technologies, Compustat

[Table 2] computes long-short returns based on decile portfolios and their alphas. Panel A uses value-weighted portfolio returns where Panel B uses equal-weighted series.

Alphas are not significant both in Panel A and Panel B in the case of size factor which implies there would be little advantage to use the tilting with this factor. Though value factor has no significance in equal weighted portfolio, its FF3F's alpha is negatively significant. While excess return is not significant for momentum, it has statistically positive significant CAPM and FF3F alphas. It indicates momentum works relatively well compared to size and value factor.

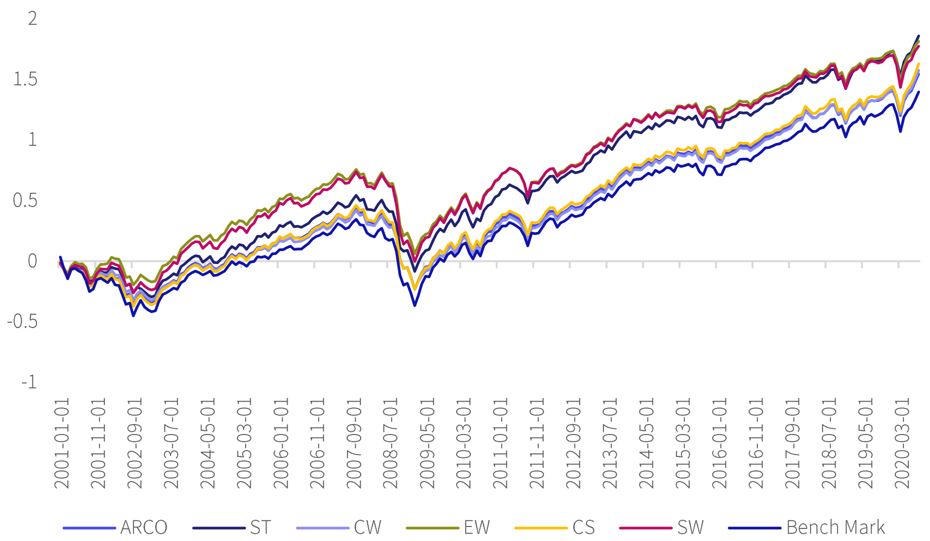
Above tests show momentum's return increases as we divide universe into more baskets, [Figure 5] and it has significantly positive CAPM and FF3F's alphas. Hence, we conclude momentum is robust and we apply tilting methodologies to this factor as our main analysis. Appendix 1 and 2 contains the same result for value and size.

[5] William F. Sharpe. ,1964, Capital Asset Prices : A Theory of Market Equilibrium under Conditions of Risk, The Journal of FINANCE 6-3, 425-442
[6] Fama, E. F., French, K. R. , 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3-56
[7] Whitney K. Newey and Kenneth D. West., 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Econometrica 55-3, 703-708

2. Tilting Performance based on Methodology

We apply tilting methodologies to the momentum factor. Tilting methodologies include ARCO, ST, CW, EW, CS and SW. We use the value-weighted portfolio of the stocks in the universe as the benchmark. The sample period is from Jan 2001 to Aug 2020.

[Figure 6] Factor Long-Short Annual Return



Source: QRAFT Technologies, Compustat

[Table 3] Basic Result Based on Methodology

	Ann CAGR	Ann Std	Ann Sharpe	MDD	Win Ratio
Benchmark(BM)	0.0635	0.1535	0.4801	-0.5101	0.6500
CW	0.0714	0.1425	0.5573	-0.4794	0.6500
CS	0.0730	0.1518	0.5425	-0.5008	0.6375
ARCO	0.0699	0.1458	0.5383	-0.4894	0.6333
ST	0.0872	0.1475	0.6436	-0.4674	0.6458
EW	0.0903	0.1548	0.6390	-0.5023	0.6583
SW	0.0861	0.1663	0.5833	-0.5228	0.6250

Source: QRAFT Technologies, Compustat

[Figure 6] shows the cumulative return for each methodology where all of them outperform the benchmark. However, [Table 3] shows the performance is different for each methodology. Hence, to compare the details for each series, we study the effectiveness based on excess return, factor exposure, and turnover.

Every tilting methodology adjusts weights within the benchmark to fully exploit the effectiveness of the factor, which leads to higher chance of raising tracking error. Hence, it is crucial to analyze the tradeoff between excess return and the tracking error .

[Figure 7] Excess return & Tracking Error

Source: QRAFT Technologies, Compustat

[Figure 7] compares annual excess returns and tracking errors for each methodology from Jan 2001 to Aug 2020. We observe there is a positive correlation between the excess return and the tracking error. While ARCO, CW, and CS have relatively small tracking errors, SW, ST and EW have larger tracking errors and thus, have higher excess returns.

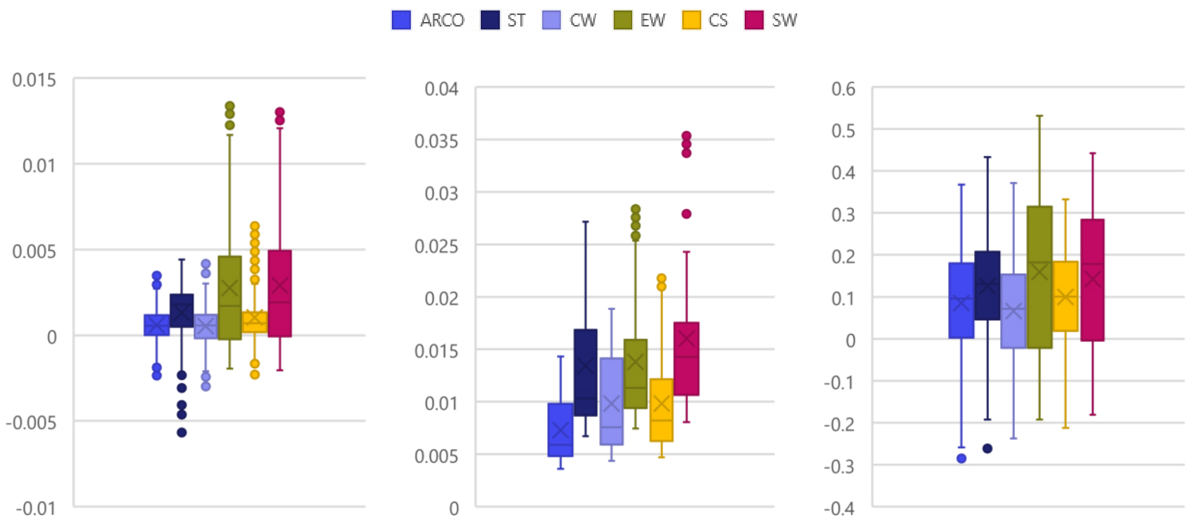
[Table 4] IR Table for the whole period

	Avg Return	Excess Return	Tracking Error	Information Ratio
Benchmark(BM)	0.0069	-	-	-
CW	0.0075	0.0006	0.0105	0.0584
CS	0.0079	0.0009	0.0092	0.1025
ARCO	0.0074	0.0005	0.0074	0.0698
ST	0.0088	0.0019	0.0135	0.1394
EW	0.0087	0.0018	0.0139	0.1291
SW	0.0087	0.0018	0.0148	0.1196

Source: QRAFT Technologies, Compustat

Information ratio is defined as the excess return over the tracking error and it measures how consistently the portfolio outperforms the benchmark along its tracking error. [Table 4] suggests ST has the highest information ratio (0.1394) while CW has the lowest one (0.0584). As every tilting methodology has a positive ratio, it implies the significance of the tilting exists.

[Figure 8] 3-year rolling Excess Return(Left) / Tracking Error(Middle) / Information Ratio(Right)



Source: QRAFT Technologies, Compustat

[Table 5] 3-year rolling IR Table

	3y rolling Avg Return	3y rolling Excess Return	3y rolling Tracking Error	3y rolling Information Ratio
Benchmark(BM)	0. 0061	-	-	-
CW	0.0066	0.0005	0.0098	0.0659
CS	0.0071	0.0010	0.0098	0.0997
ARCO	0.0067	0.0006	0.0073	0.0855
ST	0.0074	0.0013	0.0134	0.1253
EW	0.0089	0.0028	0.0138	0.1592
SW	0.0090	0.0029	0.0160	0.1426

Source: QRAFT Technologies, Compustat

[Figure 8] shows the distribution of 3-year rolling return, TE, and IR for each methodology. As the performance might be distorted by certain events if the sample period is long enough, it may be more suitable to use the 3-year rolling series. [Table 5] compares 3-year rolling statistics where we can check the tendency for each methodology. It shows that unlike in [Table 4] EW has the highest IR (0.1592) while CW has the consistently lowest IR.

There are two ways to compute factor exposure. We can use information of the constituents of the portfolio where we multiply the factor score of each constituent with its weight. Active factor exposure is defined as the product of the factor score and the difference in weights used in the portfolio and the benchmark as follows.

$$Facotr\ Exposure = \sum_{\mathrm{i}=0}^{n} Z_{\mathrm{i}} \times w_{p,\mathrm{i}}$$

$$Active\ Factor\ Exposure = \sum_{\mathrm{i}=0}^{n} Z_{\mathrm{i}} \times (w_{p,\mathrm{i}} - w_{B,\mathrm{i}})$$

Where Z_i is the factor score, $W_{p,i}$ and $W_{B,i}$ are the weights in the portfolio and the benchmark, respectively. Factor exposure is the value-weighted sums of each product. To do so, we need to first compute the weight in the portfolio and the factor score.

An Alternative method to compute factor exposure is to use the portfolio return. We estimate the coefficients (beta) from regressing the portfolio on multiple factors (e.g. factors used in FF3F). As it does not require the factor score and the weight for each stock in the portfolio, it is relatively simple to compute factor exposure. However, we need to be cautious as it might produce misleading results if we use ill-defined factor models. For instance, it is crucial to use the factor computed from the investment universe only. Hence, we replicate Carhart 4-Factor(1997)[8] model using the investment universe and use these factors to compute factor exposure. Carhart 4-Factor model has one additional factor, UMD (momentum), compared to Fama-French 3 factor model. It is defined as follows.

$$EXR_t = \alpha + \beta_{mkt} MKT_t + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{UMD} UMD_t + \epsilon_t$$

EXR_t *: Excess return*

MKT_t *: Benchmark Return – Risk Free Rate (T-Bill 3-month Rate)*

HML_t *: Monthly Premium of the book-to-market factor*

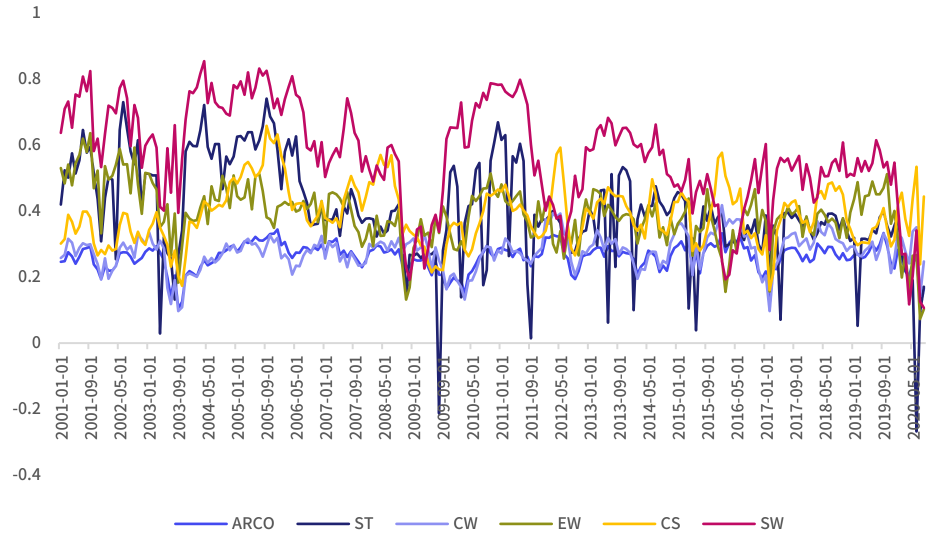
SMB_t *: Monthly Premium of the size factor*

UMD_t *: Monthly Premium on Winners minus Losers*

MKT is the excess return over the market, where it is used to estimate the market beta proposed in CAPM. HML (High Minus Low) is the value factor where we long high book-to-market stocks and short low ones. SMB (Small Minus Big) is the size factor where we long small-cap stocks and short large-cap ones. UMD (Up minus Down) is the momentum factor, where we long winner stocks whose cumulative returns of the previous 12m-1m had been higher and short loser stocks.

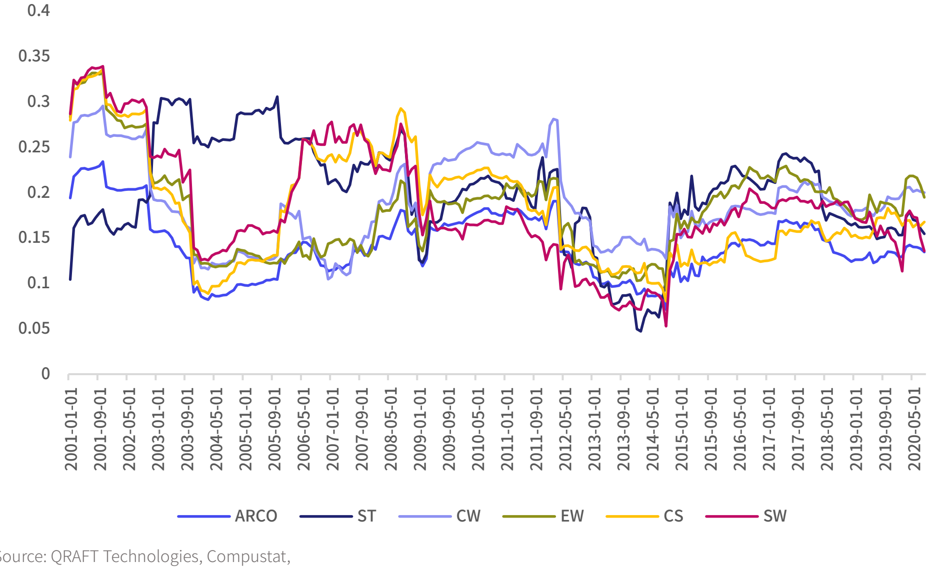
[8] Carhart M. M, 1997, On Persistence in Mutual Fund Performance, The Journal of Finance, 52-1, 57-82

[Figure 9] Active Factor Exposure



Source: QRAFT Technologies, Compustat,

[Figure 10] UMD 36 month rolling coefficient(using Carhart 4 factor model)



Source: QRAFT Technologies, Compustat,

[Figure 9] shows the change the Active Factor Exposure, [Figure 10] presents the coefficient on UMD from Carhart 4 Factor Model using 3-year rolling series. The figures suggest that the result varies depending on methods to compute the exposure. We analyze the effectiveness of these 2 Factor exposure.

[Table 6] Tilting Active Factor Exposure validation

The table represents t-test of active factor exposure and its p-values

	CW	CS	ARCO	ST	EW	SW
Mean	0.2775	0.3900	0.2610	0.4003	0.3899	0.5703
t-statstics	74.5495	67.3509	88.4240	41.4389	68.1255	62.0909
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Source: QRAFT Technologies, Compustat,

[Table 6] presents the result of the active factor exposure (AFE). All the tilting methodologies have significantly positive AFEs where SW and ST have relatively higher ones and ARCO and CW have relatively lower ones. It implies as both SW and ST put more weights on the stocks that have higher factor signals, they have higher AFEs.

[Table 7] Tilting Chart 4 Factor model Regression

To compute factor exposure, we use the excess return over Carhart 4 Factor Model (1997) where it uses 3 factors from Fama-French 3 factor model (1993) and momentum factor. Const represents the excess return while MKT, SMB, HML, and UMD presents factor exposures for the market, size, value, and momentum factor, respectively. 3-month T-bill return has been used as the risk-free rate (Rf) and p-values are in the parentheses.

	CW	CS	ARCO	ST	EW	SW	Benchmark
const	0.002	0.002	0.002	0.002	0.000	-0.001	0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.683)	(0.309)	(0.000)
Mkt-RF	1.030	1.092	1.061	1.043	1.087	1.157	1.122
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB(Size)	-0.008	0.047	0.021	0.167	0.594	0.683	-0.002
	(0.840)	(0.290)	(0.455)	(0.000)	(0.000)	(0.000)	(0.793)
HML(Value)	0.088	0.034	0.060	0.142	0.179	0.155	0.015
	(0.011)	(0.314)	(0.013)	(0.000)	(0.000)	(0.001)	(0.006)
UMD(Momentum)	0.204	0.190	0.150	0.243	0.201	0.198	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.557)
R-square	0.979	0.982	0.990	0.958	0.975	0.974	0.999

Source: QRAFT Technologies, Compustat

[Table 7] shows the regression results based on Carhart 4 factor model. Every tilting methodology has a positive coefficient on UMD factor, and its magnitude is larger than that of benchmark portfolio. It implies tilting has effectively increased the exposure to the factor. Consistent with [Table 6], ST has the largest factor exposure, and ARCO has the lowest exposure.

Nevertheless, two ways of computing factor exposure do have a couple of differences, as Active Factor Exposure only takes the change in weights based on each constituent into consideration, while regression-based method considers the change in constituents itself as well. Hence, it is important to use the appropriate method to compute the exposure based on different objectives.

While a tilting methodology can enhance risk-adjusted return in the long-run, a certain methodology might result in high turnover rates to maintain the tilting (Hubert et al 2019). This induces higher transaction costs which include fees, transaction tax , and market impact. Hence, when comparing tilting methodologies, it is crucial to consider the impact of transaction cost due to turnover for each methodology. Hence, we study turnover for each methodology in this section.

[Table 8] Turnover

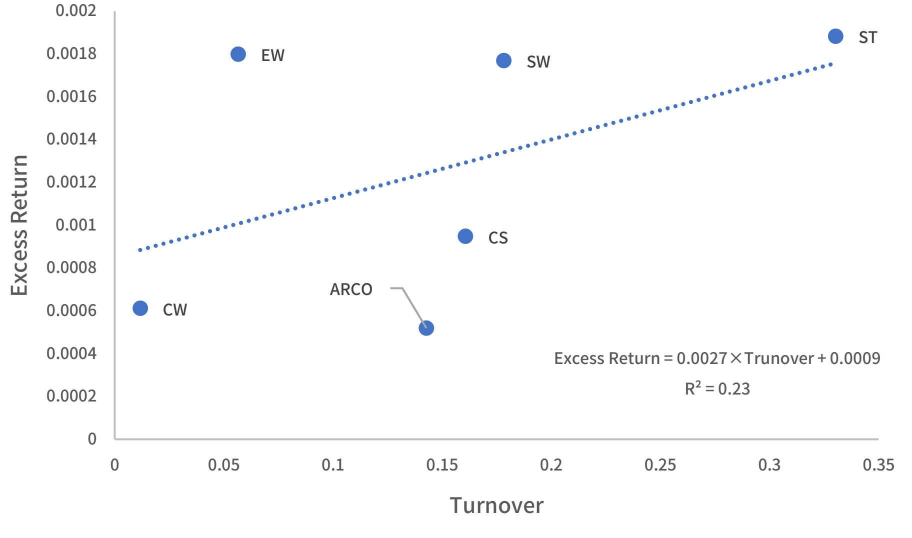
This table presents both average turnover estimates, computed using a methodology in DeMiguel et al (2009)[9] and relative turnover estimates, where we divide each average turnover by the turnover of the benchmark

	CW	CS	ARCO	ST	EW	SW
Avg Turnover	0.1368	1.9236	1.7148	3.9816	0.6756	2.1324
Relative Turnover	2.0480	32.5453	28.5905	69.6064	11.1699	36.0929

Source: QRAFT Technologies, Compustat

[Table 8] shows annual turnover estimates for each tilting methodology. CW has the lowest turnover while ST has the highest turnover. EW also shows that the turnover is quite low, because the stocks selected by the momentum signal do not change significantly. In other words, the turnover appears relatively low since all stocks are selected equally in weight while stock changes are not large. For this reason, CW and EW tend to increase turnover as stock replacements become more frequent as the market cap coverage ratio decreases.

[Figure 11] Excess Return and Turnover for Difference Tilting Methods



Source: QRAFT Technologies, Compustat

[9] Victor DeMiguel, Lorenzo Garlappi and Raman Uppal, 2009 , The Review of Financial Studies, 22-5, 1915-1953

[Figure 11] shows a relation between excess return and turnover. While the R-squared is low (23%), it roughly presents how turnover affects excess return. While it is inevitable to have higher turnover to have the larger exposure to the factor, having higher turnover rates imply it could produce higher excess returns. Hence, it is important to consider the trade-off between turnover rates and excess returns. The figure suggests EW and CW deliver relatively higher excess returns over turnover rates whereas CS and ARCO deliver lower returns.

Conclusion

This paper covers the advantage of the passive investment and how we can improve the portfolio by using factor tilting to exploit the benefits of the active strategy. We find how we expose portfolios to the factor differently using diverse tilting methodologies lead to different results. Out of many candidates, we use the momentum factor to analyze the effectiveness of the tilting as it is one of the most robust factors.

We compare the performance of each tilting methodology focusing on excess return, factor exposure, and turnover rates . In terms of excess return, every tilting methodology has a positive information ratio (IR) through the whole sample period. Signal Tilting (ST) has the highest IR (0.1394) among all of them, while Capitalization Weight (CW) has the lowest one (0.0584). In terms of factor exposure, we use two methods to compute the exposure, active factor exposure (AFE) and regression-based approach. Every tilting methodology has a significantly positive AFE where Signal Weighting (SW) and ST have relatively higher values and Active Risk Constrained Optimization (ARCO) and Capitalization Weight (CW) have relatively low values. To apply regression-based approach, we use Carhart 4-factor model. Consistent with AFE approach, every tilting methodology has a significantly positive exposure, and its magnitude suggests the tilting has increased the exposure to the factor compared to the benchmark. In terms of turnover rates, CW has the lowest turnover where ST has the highest.

The results shown in this paper has a limitation that they are constrained to the momentum factor. Additional tests have to be conducted based on approaches suggested in this paper when applying tilting to different factors. We expect results would be different based on diverse characteristics of each factor. Hence, the optimal tilting methodology may vary depending on investment objectives.

We expect analysis shown in this paper can help investors understand characteristics of various methodologies and choose the optimal portfolio. As there are numerous tilting methodologies and factors, there can be endless number of portfolios. Tests have shown we can improve risk-adjusted returns based on the tilting. As there is a growing interest in smart beta ETFs by several global asset management companies, we expect the tilting methodology to be adopted in various perspectives in this field.

Appendix 1

Size Factor

Information Ratio

Source : Qraft Technologies, Compustat

	3y rolling Avg Return	3y rolling Excess Return	3y rolling Tracking Error	3y rolling Information Ratio
Benchmark	0. 0061	-	-	-
CW	0.0066	0.0004	0.0029	0.1446
CS	0.0098	0.0037	0.0228	0.1626
ARCO	0.0067	0.0006	0.0071	0.0780
ST	0.0079	0.0018	0.0118	0.1308
EW	0.0070	0.0009	0.0067	0.1176
SW	0.0081	0.0020	0.0127	0.1339

Active Factor Exposure t-test

	CW	CS	ARCO	ST	EW	SW
Mean	0.2479	1.6786	1.0019	1.5093	0.9407	1.5771
t-statstics	193.6012	165.9849	138.0851	151.0476	164.8383	157.5682
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Carhart 4-factor regression

	CW	CS	ARCO	ST	EW	SW	Benchmark
const	0.0008	-0.0008	0.0001	-0.0009	0.0000	-0.0011	0.0012
	(0.000)	(0.388)	(0.885)	(0.049)	(0.984)	(0.020)	(0.000)
Mkt-RF	1.1442	1.2200	1.1740	1.2206	1.1728	1.2285	1.1215
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB(Size)	0.1612	0.9536	0.2691	0.6652	0.3423	0.7317	-0.0023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.793)
HML(Value)	0.0310	0.1731	0.0813	0.1146	0.0757	0.1197	0.0154
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
UMD(Momentum)	-0.0034	-0.0993	-0.0048	-0.0212	-0.0068	-0.0242	0.0019
	(0.443)	(0.025)	(0.671)	(0.106)	(0.435)	(0.078)	(0.557)
R-square	0.9980	0.8952	0.9871	0.9878	0.9931	0.9873	0.9987

Turnover

	CW	CS	ARCO	ST	EW	SW
Avg Turnover	0.5021	4.0177	0.1266	0.6755	0.2682	0.8130
Relative Turnover	7.8589	71.3416	1.6900	11.3217	4.2661	13.6088

Appendix 2

Value Factor

Information Ratio

Source : Qraft Technologies, Compustat

	3y rolling Avg Return	3y rolling Excess Return	3y rolling Tracking Error	3y rolling Information Ratio
Benchmark	0. 0061	-	-	-
CW	0.0066	0.0003	0.0057	0.0404
CS	0.0098	0.0002	0.0168	0.0060
ARCO	0.0067	0.0004	0.0076	0.0094
ST	0.0079	0.0021	0.0136	0.1268
EW	0.0070	0.0001	0.0077	0.0289
SW	0.0081	0.0023	0.0151	0.1317

Active Factor Exposure t-test

	CW	CS	ARCO	ST	EW	SW
Mean	0.2854	0.4610	0.2923	0.3601	0.4694	0.5951
t-statstics	59.8010	38.9143	55.5559	61.0400	41.2567	47.5964
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Carhart 4-factor regression

	CW	CS	ARCO	ST	EW	SW	Benchmark
const	0.0018	0.0004	0.0015	0.0000	0.0015	0.0000	0.0012
	(0.000)	(0.727)	(0.000)	(0.934)	(0.000)	(0.940)	(0.000)
Mkt-RF	1.1365	1.1893	1.1330	1.2109	1.1791	1.2602	1.1215
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB(Size)	-0.0134	0.2196	0.0209	0.6111	-0.0101	0.6056	-0.0023
	(0.199)	(0.000)	(0.397)	(0.000)	(0.616)	(0.000)	(0.793)
HML(Value)	0.1530	0.2634	0.1814	0.2693	0.1544	0.2655	0.0154
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
UMD(Momentum)	-0.0361	-0.0967	-0.0581	-0.0589	-0.0726	-0.1072	0.0019
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.557)
R-square	0.9958	0.9245	0.9891	0.9840	0.9896	0.9792	0.9987

Turnover

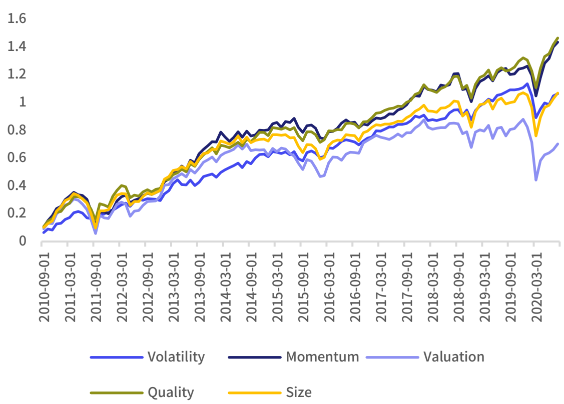
	CW	CS	ARCO	ST	EW	SW
Avg Turnover	0.5682	2.8671	0.1384	0.6496	0.6379	1.3272
Relative Turnover	8.8484	50.7092	1.9085	10.8786	10.3524	22.0446

Appendix 3

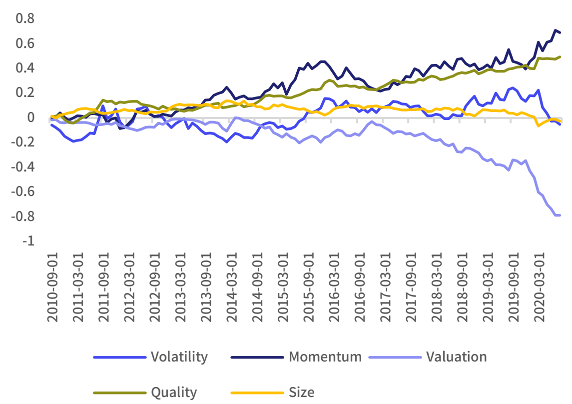
Factor Performance

- In terms of volatility, we use the inverse of the volatility of 36-month return. In terms of valuation, we use the equal weight of the inverse of PER, PBR, and PCR. Size uses the inverse of the market-cap, momentum uses the 12m-1m return, and quality uses the equal weight of ROE, ROA, and GPA.
- Long-Only presents long top quintile portfolio and Long-short shows the return series of the long-short quintile portfolio.

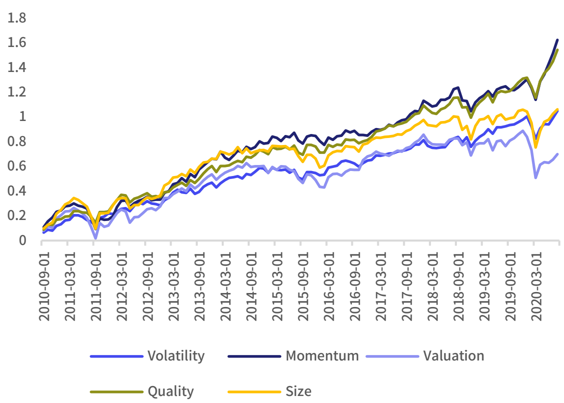
Equal Weight Long-Only



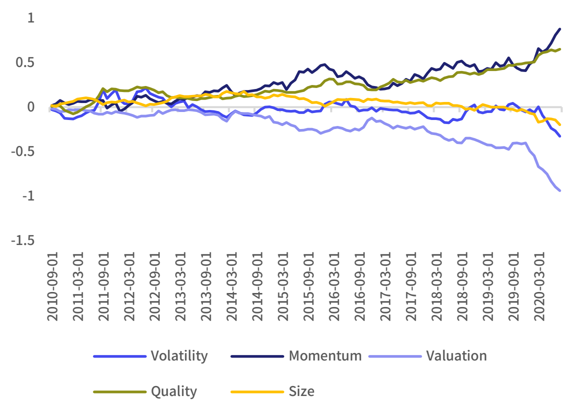
Equal Weight Long-Short



Value Weight Long-Only



Value Weight Long-Short



Source : QRAFT Technologies, Compustat