A Practitioner's Guide to Multi-Factor Portfolio Construction

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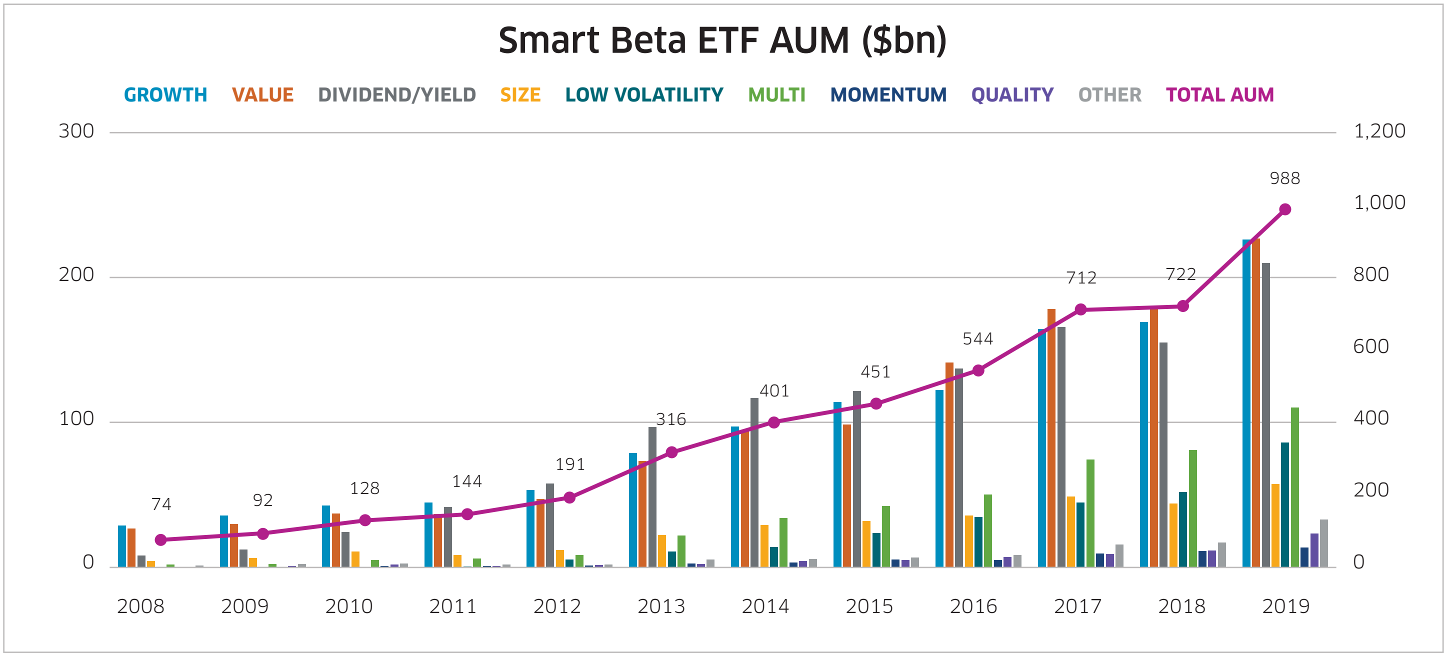
Summary

- Diversifying with multi-factor approaches can better help factor investors harvest more robust, long-term alpha.
- There are three common approaches to construct multi-factor portfolios: Heuristic, Optimized or Risk-Based.
- The Heuristic approach uses equally weighed factor scores to pick stocks. It is the simplest construction; however it may have higher tracking errors, is not as efficient in generating alpha, and has the worst risk-adjusted performance.
- The Optimized approach tries to solve a security-based large-scale mean-variance optimization. It can lead to a black-box problem due to the model complexity. Modeling security correlation is also very difficult and can significantly lower the reliance of optimization process.
- The Risk-Based approach models the portfolio expected return on a weighted basket of factor risk premiums. The factor loadings are time-varying and selected based on portfolio managers' views about the factor performance, risk budget and internal / external investment resources.
- In the last section of the paper, we presented a Risk-Based Multi-factor model portfolio that outperformed both the benchmark and the equal factor weighted model. If managing with beta exposure, the enhanced model can improve the total return with only marginal increase of volatility, and hence further improve the risk-adjusted performance.

Introduction to Factor Investing

Investors are increasingly adopting an alternative weighted indexing approach to traditional capital weighting. Factor Investing, a.k.a. Smart Beta based strategies, are growing at a tremendous pace and have won investors' hearts.

Factor Investing has Experienced Great Success in the Last Decade



Source: Bloomberg Data as of December 31, 2019

Mark Marex, CFA, my colleague at Nasdaq, recently published an excellent article to explain what factors are and how to invest in them[1]. He describes factors as the "drivers of success" and building blocks in investment returns. Just like in many team sports, coaches need to pick the "right" players for the "right" game, investors shouldn't expect any one single factor to win every time, but should consider employing a multi-factor approach for a more persistent, long-term outperformance over the benchmark.

Yearly Rankings of Factor Performances

2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
					Y											
M					S	S										
S	M			Q	Q	M	Q	S	Y		Q					
Q	S		M	S	M	Y	Y	G	S		G	S	G		Q	
V	Q	S	Q	Y	G	V	S	M	Q	G	M	V	Q	G	M	G
Y	G	V	G	V	V	Q	V	Q	V	Q	S	Y	M	Q	G	M
B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B
G	Y	M	V	G		G	M	Y	M	V	V	Q	Y	M	V	Q
	V	Y	S	M			G	V	G	M	Y	G	V	S	Y	V
		Q	Y							Y		M	S	V	S	S
		G								S				Y		Y

Source: Nasdaq Calculation with YTD as of June 30, 2020

1. Factor 101: What is a Factor, and How/When/Why to Invest in One? Mark Marex, CFA (2019).

Nasdaq Factor Indexes

FACTOR	CODE	PROXY INDEX	INDEX NAME
Benchmark	B	NQUS500LCT	Nasdaq US 500 Large Cap Index
Growth	G	NQUS500LCGT	Nasdaq US 500 Large Cap Growth Index
Quality	Q	NQPRCET	Nasdaq US Price Setters Index
Yield	Y	NQSHYLT	Nasdaq US Shareholder Yield Index
Momentum	M	DWTLTR	Dorsey Wright Technical Leaders Index
Value	V	NQUS500LCVT	Nasdaq US 500 Large Cap Value Index
Size	S	NQUSSLT	Nasdaq US Small Cap Select Leaders Index[2]

In this paper, we try to summarize the best practices of multi-factor portfolio construction given Nasdaq's more than a decade's dedication to the smart beta indexing business and our continuous collaborations and partnerships with industry's leading asset managers.

Heuristic Multi-factor Construction

Multi-factor strategies are not created equally. One of the common ways to create multi-factor weightings is to apply a simple heuristic approach. For example, suppose that we were able to calculate all five factor scores for every individual stock in our universe. A heuristically derived comprehensive factor score for any stock could look like the following:

$$\alpha_i = 0.2 * F_{1,i} + 0.2 * F_{2,i} + 0.2 * F_{3,i} + 0.2 * F_{4,i} + 0.2 * F_{5,i}$$

Where, $F_{j,i}$, is the factor exposure of each security i for target factor j.

You then can pick, for example, the top 500 scored stocks and weight them either by market cap, equally or by the overall factor scores.

The most distinguished advantage of a multi-factor heuristic weighting approach is simplicity. It does not require one to use the sophisticated optimization tool and it does not intend to bet on the outperformance of any single factor. However, this also means that the heuristic multi-factor construction approach will, a.) have higher tracking errors, b.) not be the most efficient way to generate alpha (factor active return), and c.) have the worst risk (tracking error) adjusted performance (alpha).

> *"The heuristic multi-factor construction approach will, a.) have higher tracking errors, b.) not be the most efficient way to generate alpha, and c.) have the worst risk (tracking error) adjusted performance (alpha)."*

A heuristic multi-factor portfolio may not track a benchmark well because it uses simple mathematics to combine the factor scores. An alternative way to more efficiently control portfolio active risk is to feed your screened stocks into an optimization process. However, you will lose the beauty of simplicity in the model and become invulnerable to various modeling risks and errors.

A heuristic multi-factor portfolio tries to treat each factor equally and avoid betting on any single factor at any time. But avoiding any major risk may cause the portfolio to have performance that not so different from the benchmark. When combined with the relatively large tracking errors that the heuristic approach bears, the portfolio actually may deliver a worse risk-adjusted alpha performance over time.

2. Since Dorsey Wright Technical Leaders Index history starts from 2007, we used another similar Dorsey Wright Index, Dorsey Wright Dynamic Focus Five Total Return Index (DWANQDFFT), to extend the return history.

Optimized Multi-factor Construction

One obvious remedy for the heuristic multi-factor approach is to introduce an appropriate risk framework and use large scale optimization to tilt the (expected) portfolio risk to a satisfied range within that of the benchmark. Portfolio modelers will also apply various security and sector level constraints in order to achieve sufficient diversification. The objective function for the minimal risk optimization could look like this:

$$\min_{W} \bar{\sigma}_p = W^T \Sigma W$$

Subject to

$$0 \leq w_i \leq j \textit{ for every stock } i$$

$$sum(w_i * f_{k,i}) = F_k \textit{ for every factor } k$$

$$sum(w_i * s_{l,i}) = S_l \textit{ for every sector } l$$

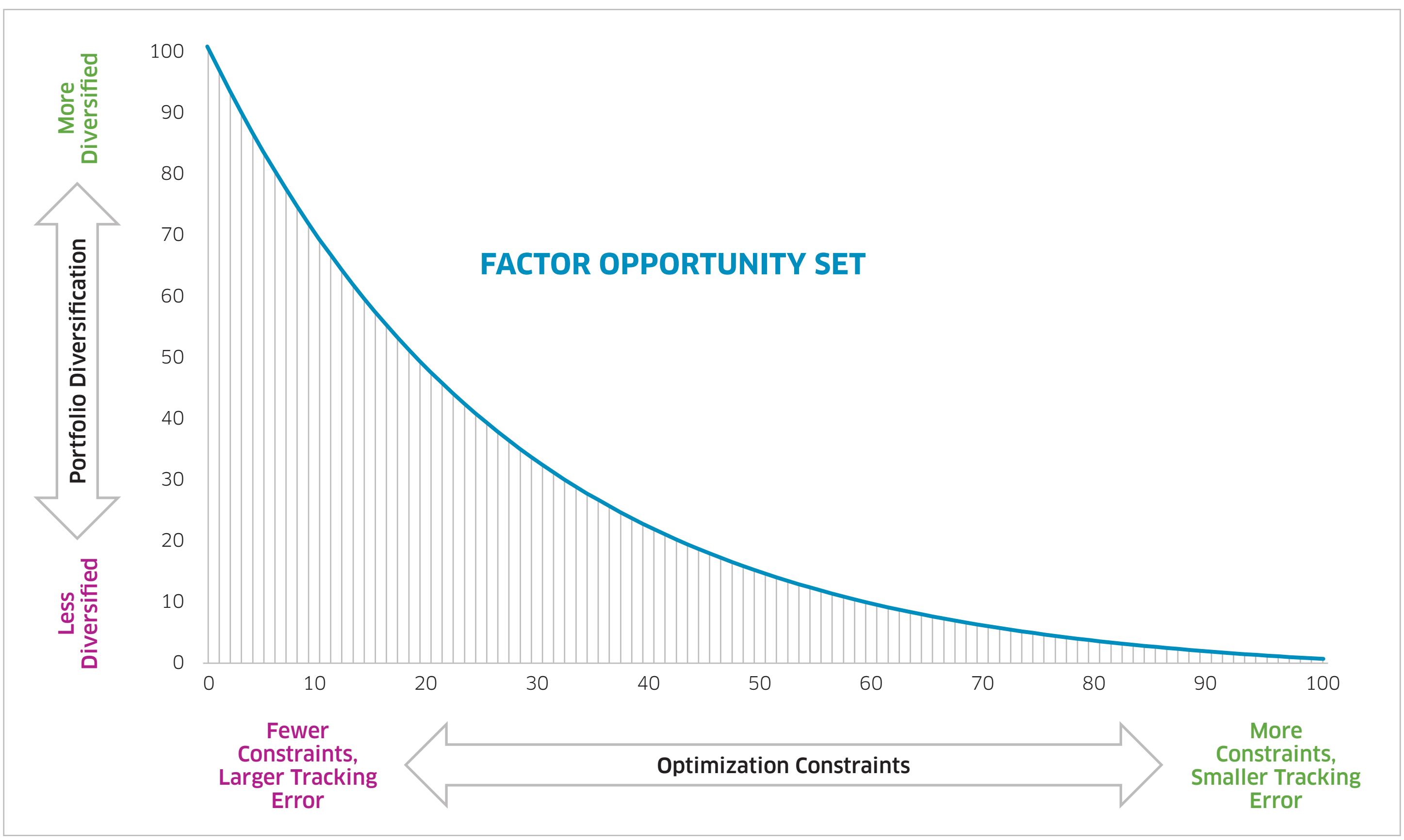
$$sum(w_i) = 1$$

Where, Σ is the security covariance matrix and $\bar{\sigma}_p$ is the expected portfolio tracking error that aims to minimize.

Building a robust optimization model is not an easy task. For any given set of pre-screened factor securities, which contain a fewer number of stocks but a more distorted risk profile than the benchmark, optimization modelers have to instantaneously face two opposite tasks: controlling diversification and controlling tracking error. Putting in more constraints will lead to smaller tracking error, but with fewer stocks satisfying the overall constraints, the portfolio can become overly concentrated. The opposite is also true: loosening the constraints will help portfolio diversification, but the tracking error will also become larger.

The Dilemma of the Optimization Problem

The hypothetic illustration of the relationship between the two tasks in portfolio optimization: Portfolio Diversification and Optimization Constraints. 0 to 100 indicates the lowest to the highest possible levels.

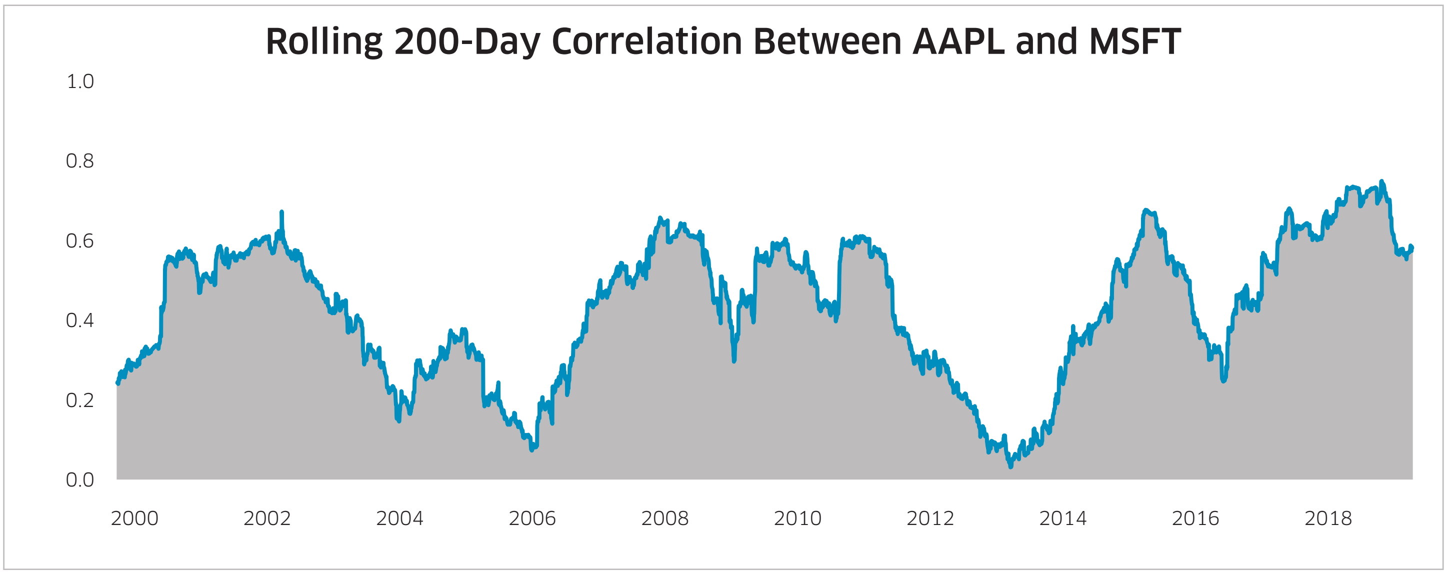


Indeed, there's no single best solution for all the portfolio optimization problems. Portfolio modelers have to apply their best practices to build their optimized multi-factor strategies. Sometimes, the level of model complexity in optimization can lead to a black-box problem: it becomes much harder to justify the fair exposure of any stock in an optimized portfolio.

> *"The level of model complexity in optimization can lead to a black-box problem: it becomes much harder to justify the fair exposure of any stock in an optimized portfolio."*

What makes the optimized multi-factor approach more vulnerable to modelling errors is the calculation of covariance matrix. Security based large-scale optimization relies on the correct prediction of the correlation of every pair of securities. As security prices are consistently influenced with different market information and changing investor sentiments, to correctly model the security correlation is a very difficult task, if not entirely impossible. Even for AAPL and MSFT, the two of the largest caps and most liquid stocks on the market, their long-term (200 days) correlations can range from nearly 0 to 0.74, and swing sharply in short horizons.

Security Correlation is Unstable and Very Difficult to Predict



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Risk-Based Multi-factor Construction

The problems with security-based large scale optimization (a.k.a. Markowitz Optimization, mean-variance optimization, modern portfolio theory) are actually widely understood by academics and several remedies have been proposed and won great popularity (including Nobel Prizes).

CAPM:

The Nobel winning capital asset pricing model (CAPM)[3] proposed using only the market risk premium (Beta) to

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

La formule est assez logique, prend en compte la sensibilité au marché

model the undiversified risk of a security and greatly reduce the optimization task to a linear regression:

Where, $E(R\_i)$ is the expected return of stock I, R_f is the risk-free interest, β_i is the stock i's sensitivity to market, and R_m is the market expected return.

3. Sharpe, Markowitz and Merton Miller jointly received the 1990 Nobel Memorial Prize in Economics for this contribution to the field of Financial Economics.

Fama-French:

Fama-French improved CAPM and uses three factors to explain the security's undiversified risk: market (Beta), size (SMB) and value (HML). It won the Nobel Prize in 2013.

$$E(R_i) = R_f + \beta_i\big(E(R_m) - R_f\big) + b_{s,i} * SMB + b_{v,i} * HML$$

Where, SMB is the expected excess return for small minus big companies (Size), and HML is the expected excess return for high minus low book/market companies (Value).

APT:

Arbitrary pricing theory (APT) further generalized the assumption for risk factors and risky assets returns to be modelled upon a basket of uncorrelated factor risk premiums. Assuming that there are no risk factors, APT believes that the expected return for any of the m stocks can be explained by using a multivariate linear regression:

$$E(R_i) = R_f + \sum_{j=1}^{n} b_{j,i} * f_j$$

Where, f_j is the risk premium of factor j, and $b_{j,i}$ is the sensitivity (factor loading) of stock i to factor j.

Since the portfolio expected return is the weighted aggregated sum of individual stock's expected returns:

$$E(R_p) = \sum_{i=1}^{m} w_i * E(R_j)$$

We now have portfolio expected return that is depending on a weighted basket of factor risk premiums.[4]

$$E(R_p) = \sum_{j=1}^{n} \lambda_j * f_j$$

The above formula is also the theoretical foundation for modern-day factor investing strategies. Although it looks similar to the formula we use to aggregate scores in the Heuristic approach, there are two major differences:

1. The R and f used in APT are explained in terms of returns and come with risk estimates, while the scores in Heuristic approach is less useful in practical portfolio construction.
2. The portfolio factor loading λ does not need to be equal across factors, in some cases does not need to be constant across time. It can be easily tilted to reflect portfolio managers' views about factor performance and risk budget.

> *"According to APT, portfolio expected return depends on a weighted basket of factor risk premiums. The portfolio factor loading does not need to be equal across factors, in some cases does not need to be constant across time. It can be easily tilted to reflect portfolio managers' views about factor performance and risk budget."*

APT can be structured practically with a risk-based multi-factor construction approach. It follows three steps:

1. Addressing the favored / un-favored factor views based on risk and return forecasts, and deciding the factor relative exposures (source of Alpha).
2. Finding the ideal investment strategies for every favored factor based on risk, return, style or other quantitative and qualitative criteria. The ideal candidates for hire can be either internally or externally managed accounts, systematic or human expert managed strategies, or follow a hybrid approach.
3. Defining the total undiversified portfolio risk-level (Beta) you want to budget in to reflect your views on the total capital market.

4. The risk-free interest term R_f is combined into factor risk premiums for simplicity.

Process for Risk-Based Multi-factor Construction

Addressing Factor Views
- Access factor risk / return
- Decide factor relative exposure (Alpha)

Building Factor Sleeves
- Single factor based strategies
- Internal vs. external, systematic vs. discretionary

Controlling Portfolio RisK
- Budget undiversified portfolio risk (Beta)
- Reflect total market view

In practice, the investable factor strategies, especially those with long-only constraints, are different from the theoretic factor risk premium numbers since they have correlations. The factor correlation is a combination of the undiversified portfolio risk (Beta) and the diversifiable factor risk (tracking error). We controlled the overall portfolio beta level in step three and we have decided in step one which factor is our favorite and what level of factor risk (tracking error) is worth carrying. So, the actual factor correlations are less worrisome in practice.

> *"Since we control the overall portfolio beta risk, and we select the favorite factor risk to carry, the actual factor correlations are less worrisome in practice."*

Demonstration on Risk-Based Multi-factor Construction

In the previous section, we briefly summarized the three different approaches for multi-factor portfolio construction:

1. Heuristic Multi-factor Construction, which uses equally weighed factor scores to pick stocks, will have higher tracking error, is not the most efficient way to generate alpha, and has the worst in risk (tracking error) adjusted performance (alpha).
2. Optimized Multi-factor Construction, which tries to solve a large scale security based mean-variance optimization problem, can lead to a black-box problem because of the model complexity. Modeling security correlation is also a very difficult task, which may significantly lower the reliance of optimization process.
3. Risk-Based Multi-factor Construction models the portfolio expected return on a weighted basket of factor risk premiums. The factor loadings are time-varying and selected based on portfolio managers' views about the factor performance and risk budget.

Given the above observations, we are very interested in building a multi-factor strategy with the risk based approach.

Constructing Risk-Based Multi-factor Portfolios

To construct a risk-based multi-factor portfolio, we need to first address the factor views in order to decide the relative exposures among factors. In this paper, we decided to implement a simple model based on the factors' three-year alpha rankings. Alpha is the industry's golden standard of measuring factor outperformance unrelated to a benchmark. We also believe that using a three-year lookback window well suits our goal of limiting transaction costs and focusing on medium-to-long term values.

Once we have accessed all the factor opportunities and picked our favorite factors, the next step is to build factor sleeves. What's extremely flexible about the risk-based approach is that you can choose to build your own factor strategies from either applying a quantitative model or work with your own fundamental research team. If you have a lack of expertise in-house, you can easily outsource that factor sleeve to the most talented managers in the industry. This mix and match approach makes sure that you can optimize the firm's all-internal / external investment resources to maximize fund performance. This is the distinct advantage that none of the heuristic or optimized Multi-factor strategies can approach.

In this paper, we built the Risk-Based Multi-factor demonstration portfolio by using the Nasdaq Factor Index Suite as the factor investing vehicles. The Nasdaq Factor Index Suite contains six investment industry widely recognized smart beta factors and with history backed to April 2004. These smart beta factors are: Growth, Value, Quality, Yield, Momentum and Size (see the full list of Nasdaq Factor Indexes on page 3). At the end of every month, we will re-calculate factor alpha based on the rolling three year factor monthly returns. With the updated view for all the factors, we then can finally select the top four best performed factors and assign them with equal dollar weights. For comparison purpose, we also constructed an equal-factor-weighted portfolio by assigning equal dollar weights to all six factors.

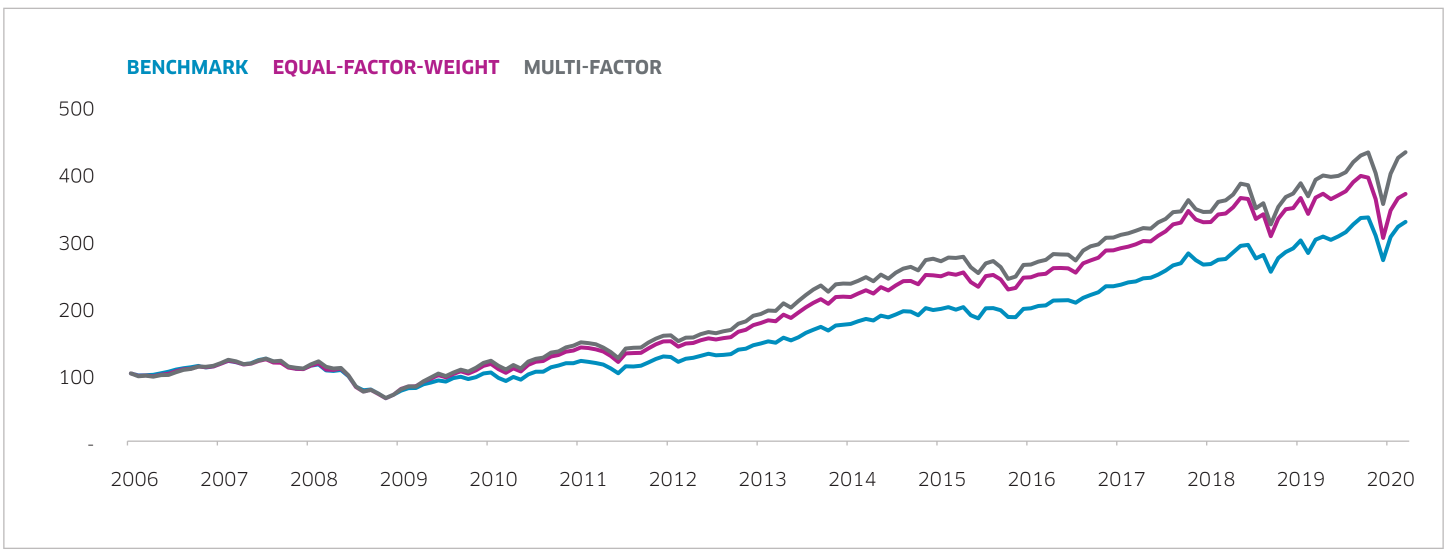
> “We built the Risk-Based Multi-factor demonstration portfolio by using the Nasdaq Factor Index Suite as the factor investing vehicles, and by assessing their three year alpha performances to form factor views.“

Accessing the Performance

Our first test with simulated multi-factor portfolio has shown good results. The multi-factor portfolio was able to outperform both equal-factor-weight and benchmark with approximately the same level of volatilities but much better returns. It outperforms the equal-factor-weight with on average 1.2% per annum and outperforms the benchmark with on average 2.1% per annum.

Risk-Based Multi-factor Portfolio Outperformed both Equal-Factor-Weight and Benchmark

The Benchmark is Nasdaq US Large Cap 500 Total Return Index (NQUS500LCT). The Equal-Factor-Weight portfolio equal weights all six factors in universe and rebalances on monthly basis. The Multi-factor portfolio is also monthly rebalanced; and it equally weights the top 4 factors by their rolling three year alpha performances



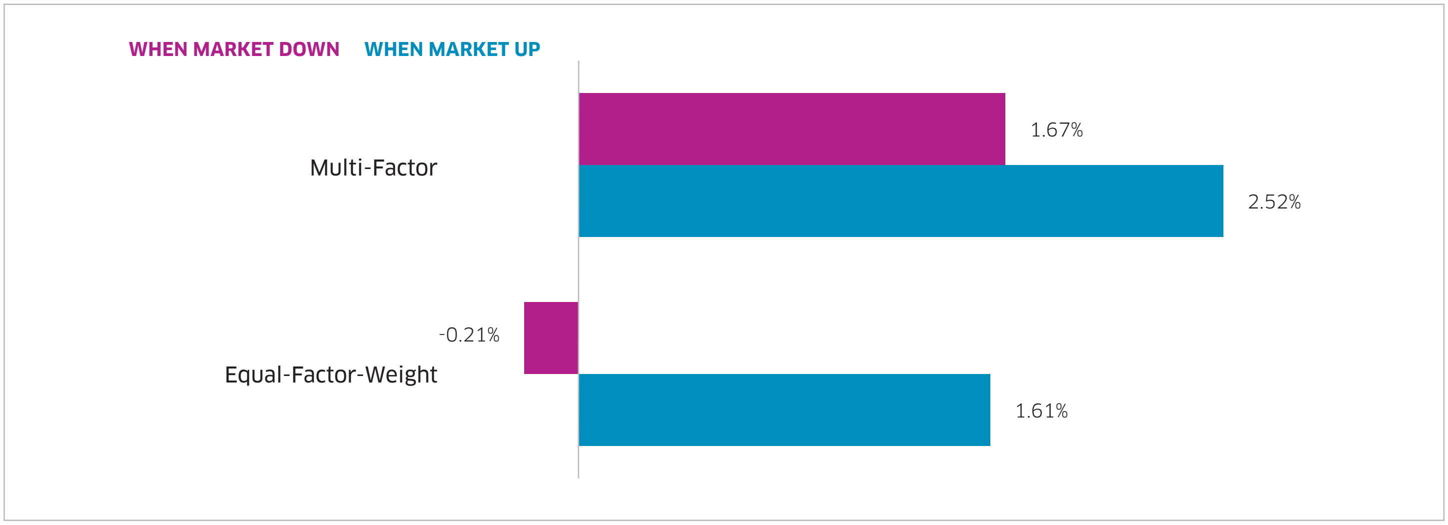
	BENCHMARK	GROWTH	QUALITY	YIELD	MOMENTUM	VALUE	SIZE	EQUAL-FACTOR-WEIGHT	MULTI-FACTOR
Annual Total Return	8.8%	9.5%	11.3%	9.3%	8.8%	7.9%	10.6%	9.7%	10.9%
Annual Volatility	14.9%	14.8%	14.0%	19.5%	17.0%	16.0%	19.5%	16.1%	15.8%
Annual Sharpe	0.59	0.64	0.81	0.48	0.51	0.49	0.54	0.60	0.69

Source: Nasdaq backtest from April 30, 2006 to June 30, 2020. All performance numbers are annualized.

We also conducted a simple scenario analysis by comparing the relative performances under the upward and downward trending markets. Specifically, we tracked the quarterly excess returns of multi-factor portfolio and its competitor, the equal-factor-weighted portfolio, over our benchmark, the Nasdaq US Large Cap 500 Index (NQUS500LCT).

Both multi-factor and equal-factor-weighted portfolios were able to outperform the benchmark (NQUS500LCT) over our measured period from June 30, 2006 to June 30, 2020. However we also found out that, from all the collected 58 sample quarters[5], the multi-factor portfolio can not only outperform the equal-factor-weighted during the market rally (when benchmark quarterly return is positive), it also outperformed during the market sell-off (when benchmark quarterly return is negative). That proves that our active factor allocation in the first step did a better job than equal weight portfolios in selecting better and less risky factors.

Risk-Based Multi-factor Worked Better in Both Directions of the Market



	EQUAL-FACTOR-WEIGHT	MULTI-FACTOR
Average Excess Return Over Benchmark	1.50%	2.21%
Average Excess Return When Market Up	1.61%	2.52%
Average Excess Return When Market Down	-0.21%	1.67%

Source: Nasdaq. Backtest history from June 30, 2006 to June 30, 2020. Quarterly excess returns are calculated over the benchmark (NQUS500LCT) and annualized.

"The risk based multi-factor was able to outperform both equal weight and benchmark with approximately the same level of volatilities but much better returns. It also did a better job than the equal weight in selecting better and less risky factors."

Improvement with Managed Beta Exposure

In the first two steps we picked our favorite factor sleeves to construct the multi-factor portfolio. These factors generated better excess returns, but also less closely tracked the benchmark. Tracking error is the "useful" type of portfolio risk that is diversifiable across factors and we are willing to carry. The other type of portfolio risk - market risk, or beta - is undiversifiable and "not so useful" in terms of alpha generation so we want to more precisely manage exposures.

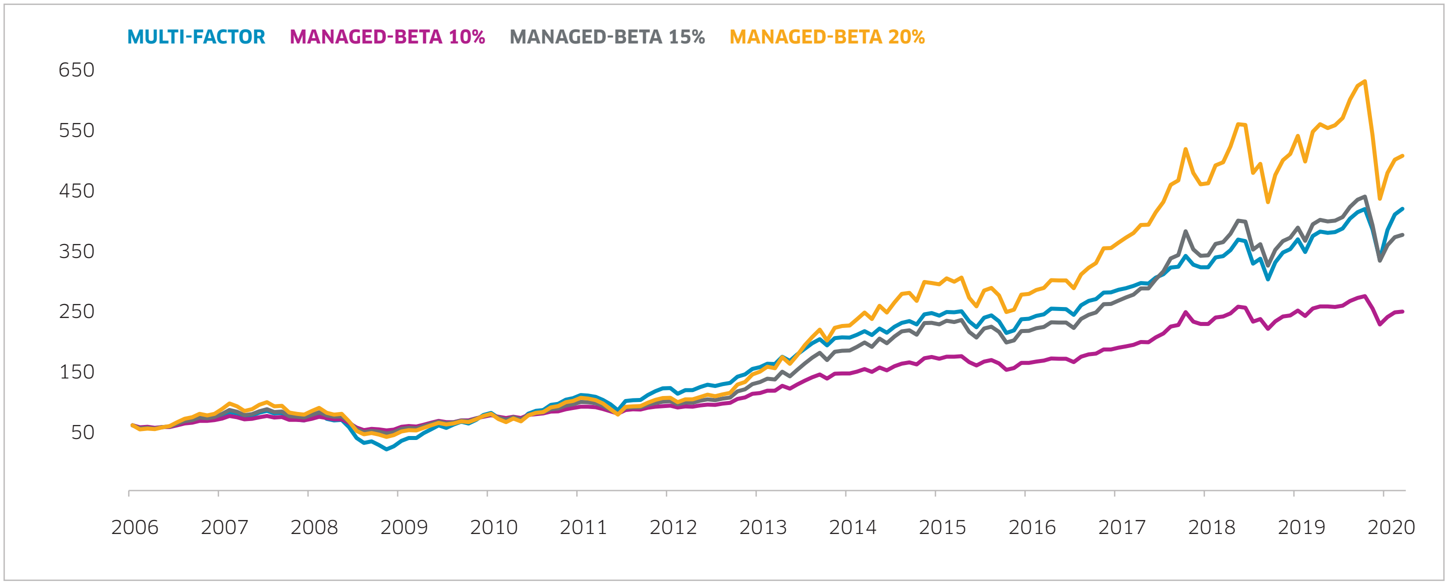
5. Despite that using quarterly frequency generated fewer samples, we believe that it is still better than using the shorter terms, such as monthly, as true representation of market trends. The monthly result will still give us the same conclusion but it suffered from too many short-term mean-reversions and hence weaker labeling problem.

There are various ways portfolio managers can manage their beta exposure. For example, one can simply sell all held stocks when facing a market correction. One approach is to keep all the stock exposures, but use broad market ETF equity futures or options to manage only the beta exposure. The obvious advantage is that you can reduce short-term turnover and transaction costs while improving downside production. However, the use of derivatives might mean that is only suitable for sophisticated investors.

In our test, we set aside 10% cash as collateral for purchasing index derivatives that can fluctuate between buying and selling 100% of the beta exposure. In regard to the desired beta exposures, we tried to match the 1-year realized portfolio beta volatility to different levels - 10%, 15% and 20% are our choices for investors' conservative, moderate-aggressive and aggressive risk sentiments.

The Original and Managed Beta Multi-Factor Portfolios

10% cash as collateral; buying or selling index derivatives up to 100% of the beta exposure; matching 1 year realized portfolio beta volatility to 10%, 15% and 20% in order to manage beta risk.



	BENCHMARK	EQUAL WEIGHT	MULTI-FACTOR	MANAGED-BETA 10%	MANAGED-BETA 15%	MANAGED-BETA 20%
Annual Total Return	8.8%	9.7%	10.9%	7.5%	10.2%	12.3%
Annual Volatility	14.9%	16.1%	15.8%	9.3%	13.5%	17.5%
Annual Sharpe	0.59	0.60	0.69	0.80	0.76	0.70

Source: Nasdaq backtest from April 30, 2006 to June 30, 2020. All performance numbers are annualized.

There are a few findings we can observe from the above results:

First, the Beta risk is still "useful" when it is carefully managed. By gradually increasing the target beta risk from 10%, 15% to 20%, we see the performance improved.

Secondly, the factor tracking errors are indeed "diversifiable". Although the tracking errors of the six individual factors are significant, ranging from 3.7% (growth) to 8.5% (size), their total contributions to the portfolio risk are negligible thanks to the factor diversifications. Indeed, our realized total portfolio risks are all lower than their targets (with buffers from 0.7% to 2.5%).

Last but not the least, reducing portfolio beta risk can help increase the risk-adjusted return, a.k.a. alpha, but the overall total return is lower. This is because factors are more efficient in delivering risk-adjusted return in alpha than in beta. With the well-known difficulty in leveraging alpha, using liquid index derivatives to managing beta exposure is a more effective solution.

> *“Manage beta exposure in a multi-factor portfolio can improve the total return with only marginal increase of volatility, and hence further improve the overall risk-adjusted return.”*

Conclusion

Factor investing has experienced great success in the past decade. There is, however, no single factor that can consistently outperform. Investors should consider employing a multi-factor approach in order to deliver more robust, long-term alpha.

Multi-factor strategies are not created equally. In this paper, we gave a brief summary of three different approaches for multi-factor portfolio construction:

1. Heuristic Multi-factor Construction, which uses equally-weighed factor scores to pick stocks, will have higher tracking error, are not the most efficient way to generate alpha, and have the worst in risk (tracking error) adjusted performance (alpha).
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3. Risk-Based Multi-factor Construction models the portfolio expected return on a weighted basket of factor risk premiums. The factor loadings are time-varying and selected based on portfolio managers’ views about the factor performance and risk budget. It also allows Mix and Match so that portfolio managers can optimize firm’s all internal / external investment resources to maximize the fund performance.

In the last section, we presented a model portfolio using the Risk-Based Multi-factor Construction approach. Our model outperformed both the benchmark and the equal weight portfolio. It also did a better job than equal weight in selecting better performing and less risky factors. If managing with beta exposure, the enhanced model portfolios can improve the total return with only marginal increase of volatility, and hence further improve the overall risk-adjusted performance.

Appendix: Factor and Model Annualized Total Returns

YEAR	BENCHMARK	GROWTH	QUALITY	YIELD	MOMENTUM	VALUE	SIZE	EQUAL-FACTOR-WEIGHT	MULTI-FACTOR	MANAGED-BETA 10%	MANAGED-BETA 15%	MANAGED-BETA 20%
2006*	9.5%	5.9%	5.0%	8.0%	3.6%	12.6%	7.3%	7.1%	6.8%	3.9%	8.2%	12.5%
2007	7.4%	9.0%	16.7%	-2.0%	19.2%	6.1%	4.2%	8.7%	11.6%	8.7%	12.2%	15.5%
2008	-35.8%	-36.0%	-31.0%	-34.3%	-45.9%	-35.4%	-31.2%	-35.6%	-37.1%	-16.6%	-24.8%	-32.4%
2009	25.8%	27.1%	34.0%	67.2%	27.2%	26.1%	47.0%	37.9%	41.0%	14.2%	17.5%	20.8%
2010	15.3%	10.6%	17.9%	23.1%	26.3%	20.6%	32.0%	21.7%	24.5%	12.7%	16.6%	20.4%
2011	2.1%	-0.1%	9.9%	6.0%	1.7%	4.2%	5.0%	4.5%	6.0%	2.6%	2.1%	1.4%
2012	15.9%	18.1%	16.9%	15.9%	17.2%	14.5%	26.3%	18.1%	19.1%	8.3%	12.0%	15.8%
2013	32.2%	30.3%	34.5%	49.8%	31.4%	34.2%	44.1%	37.3%	40.7%	32.9%	48.4%	65.4%
2014	13.5%	14.1%	13.7%	12.3%	12.9%	13.0%	12.0%	13.1%	12.1%	10.4%	16.6%	23.0%
2015	1.1%	3.2%	3.9%	-4.2%	2.0%	-0.9%	1.6%	1.0%	-0.1%	-0.8%	-1.0%	-1.4%
2016	11.8%	6.4%	7.0%	15.6%	2.9%	17.1%	22.6%	11.8%	12.0%	7.2%	10.8%	14.3%
2017	22.0%	26.3%	25.0%	19.5%	24.2%	17.7%	13.9%	21.1%	18.1%	21.7%	34.2%	39.4%
2018	-4.7%	-1.0%	-1.2%	-12.3%	-5.3%	-9.2%	-8.9%	-6.3%	-5.7%	-2.3%	-4.6%	-7.1%
2019	32.0%	32.8%	34.3%	26.8%	34.0%	30.7%	19.5%	29.8%	32.0%	19.2%	29.6%	40.5%
2020	-1.7%	9.2%	-5.3%	-18.6%	5.1%	-14.2%	-15.7%	-6.9%	1.1%	-7.1%	-12.2%	-17.3%
1Y	8.9%	18.7%	4.3%	-10.9%	12.7%	-3.0%	-11.5%	1.5%	10.6%	-1.7%	-4.0%	-6.7%
3Y	11.3%	17.1%	11.9%	0.7%	13.9%	4.2%	-0.2%	8.0%	11.3%	7.1%	9.3%	9.2%
5Y	10.9%	14.2%	11.1%	3.1%	10.5%	6.7%	3.8%	8.3%	9.6%	6.0%	8.7%	9.9%
7Y	12.3%	15.3%	12.8%	7.6%	12.6%	8.8%	8.4%	11.0%	12.2%	8.8%	12.7%	15.5%
10Y	14.1%	15.5%	15.3%	11.6%	14.6%	12.2%	13.6%	13.9%	15.2%	9.5%	13.8%	17.3%
Inception	8.8%	9.5%	11.3%	9.3%	8.8%	7.9%	10.6%	9.7%	10.9%	7.5%	10.2%	12.3%

Source: Nasdaq calculation. Definition of factors see table: Nasdaq Factor Index Suite.

* Total Return data history from April 30, 2006 to June 30, 2020