Overview

Factor investing raises plenty of questions in most investors’ minds, and rightly so. As a relatively new approach—at least in the mainstream investment world—there are several aspects that need careful consideration. This paper will address what we regard as five critical questions that investors might reasonably ask as they examine factor-based approaches:

_ Why should I consider an allocation to these strategies?
_ How do I identify good factors?
_ How do I decide how many to include?
_ What is a sound methodology for combining factors?
_ How can I compare various multifactor approaches?

Question one

Why even consider factor investing?

Figure 1 shows a simple framework for thinking about this question. It highlights some of the main features offered by three principal styles of investing—Active, Passive, and Alternative—and demonstrates our view that factor investing arguably sits at the intersection of all three, neatly encompassing some of their individual merits into one style.

Taking Active first, the clearly stated intent of this approach is to beat a benchmark. And, putting aside the voluble debate about whether or not it achieves that, the fact is that factor investors also try to beat a benchmark too (generally the “vanilla” market cap starting universe). After all, there would be little point in undertaking either Active, or Factor, investing if that wasn’t the goal. Hence, our placement of “Benchmark Outperformance” in the Active circle.

Our other bullet in there is “Research Driven”, and here our thinking is that there can often be an overlap between the two approaches because both tend to use corporate accounts, albeit in different manners. Amongst other things, an Active investor may undertake a Discounted Cash Flow (DCF) analysis for example, in which they scrutinize and forecast a company’s sales, costs and earnings, and try to draw conclusions from that about the value of the stock today. In a similar vein, certain factors, including Value and Quality as the two most obvious, also rely on accounting data. The former comparing it to market price to gauge relative “cheapness”, and the latter putting greater weight on profitability, earnings quality, asset efficiency etc.—just as an Active manager might—and preferring stocks that exhibit those characteristics.

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ETF strategist
The two key differences between these approaches we would argue are that, first, Active management will incorporate subjective views into its analysis (sales forecasts as an example), whereas factor investing is normally rules-based (broadly speaking to factor investors following the same methodology will prefer the same stocks). And, second, Active managers are often “inch wide and mile deep” in their approach as opposed to factor investor’s “inch deep and mile wide” approach. In other words, Active managers generally hold fewer positions in very deeply scrutinized companies, while factor investing usually involves holding more positions on the basis of often quite simply defined characteristics.

Moving to Passive, it’s clear why factor investing has the first feature, “Systematic Approach”, in common. Whether it’s a mutual fund, or an ETF, simply tracking an underlying index, or whether it’s a factor strategy that has any number of complex twists, a common feature utilized is a rules-based approach. Put simply, typically there is no scope for following anything other than the mandated strategy.

The allusion that this brings to mind is that of Odysseus (the investor) resisting the Siren call (the market). Like the crafty Greek hero—aware enough of his own inability to resist the appeal of the Sirens’ music, that he insisted his own crew restrain him—so too Passive and Factor investors recognize that, by forcing themselves to be rules-based, they can avoid the temptation to change their strategies during volatile times.

And, of course, this philosophy, is the main reason for the other bullet in there—“Low Cost”. Given the relative simplicity of adhering to a pre-determined strategy, and not continually needing to research and reevaluate positions, it’s no surprise that Passive and Factor based investing tends to cost less than traditional Active management.

The last comparison is with Alternatives, and what remains top of mind here, given the vast bucket of strategies labeled in this way, is really strategies that undertake factor investing, but without a passive guise. For example, they may not track a factor based index, or be subject to quite such rigid restrictions.

Clearly “Alpha Capture” is a shared goal given their similarities, but what about the “Cutting Edge Exposures” we are referring to? Well, these really just serve as recognition of Factor investing’s roots in some of the highest echelons of academic finance. Many well-known factors have been uncovered by researchers at universities and business schools, and were originally adopted by firms that had founders or employees linked to these institutions. Today, the systematic nature of such factors has translated nicely across passive approaches, giving many more investors the ability to easily access this “Cutting Edge” heritage—hence our overlap.

In our view, these are some reasonable arguments for suggesting that Factor investing sits at the intersection of

![Figure 1: Factor Investing Combines the Best Features of Active, Passive and Alternative Approaches](image-url)

Source: DWS as of December 2016.

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Question two

It looks like a factor, and walks like a factor...but is it a factor?

It’s all too easy to venture down the road of factor investing without taking time to ask an obvious question—what actually is a factor? Well, one way to approach this, is to consider four features we believe factors need to have, and we will do this with reference to one of the key diagrams in finance—the Capital Market Line (CML).

Figure 2 shows a sketch of the CML, the straight line that links an investment in a risk-free asset to that of the market and therefore illustrates the critical tradeoff between reward and risk that all investors must face. Of course, there’s a vast amount of financial theory within it, but, for our purposes, we just want to focus on points A, B, C and D to discuss the first two of our four “required” factor features.

We start by noting that point A is clearly not a good place to be on this diagram. This point represents an investment (individual asset, asset class, strategy etc.) that has higher risk, and lower expected return than the market (labeled in the diagram as the “Market Portfolio” and often proxied by a large cap equity index). In other words Point A has a lower Sharpe ratio than the broad market. Because the slope of the line linking the risk free rate and the Market Portfolio is the Sharpe Ratio of the market, then it’s apparent that a line linking the risk free rate and Point A would be less steep (lower Sharpe Ratio). So the bottom line is, try to avoid investments like those represented by Point A.

How about Point B? Well, Point B is, of course, a far superior investment to Point A. Note that, for the same level of risk as A, it is offering a higher expected return, there is no reason not to prefer it (assuming just a mild degree of rationality—that investors prefer the potential for more vs. less return for the same risk!). But, better though Point B is and still has the same Sharpe Ratio as the market (it trades exactly on the CML). That means that it is not generating any alpha. An investor could replicate Point B by simply taking a leveraged position in the Market Portfolio.

That’s our first key factor feature—there must be an expectation of a higher Sharpe Ratio (higher risk-adjusted return) than the market (alpha generation).

Turning to Point C next, and things are starting to look interesting. Note that although Point C has a lower expected return than B (and indeed than A), crucially, it trades above the CML. That means that for its given level of risk, it has a higher expected return than A and B (or, put another way, it has a higher Sharpe Ratio and is alpha generative). The one concern with C is that it offers such a small pickup in return compared to the same risk point on the CML that it raises questions about its economic significance (we deliberately plotted it above the line, but not by much). It’s possible that the additional complexity and/or transaction costs involved in moving from the CML to Point C could erode its advantages.

That leads to our second key factor feature—higher risk-adjusted returns must be economically meaningful.

So, as expected, we are naturally led toward Point D which is, in our view, the most attractive point on the diagram. Point D is starting to represent something close to what we expect from factors—it has a meaningfully higher risk-adjusted return than the market. However, there are still two hurdles that Point D needs to jump.

First, there has to be an expectation that it will continue to trade above the CML month-after-month, and year-after-year. In other words, the alpha an investment, such as the one represented by Point D, has to offer, must be statistically significant over time. It can’t just be a transient feature that will quickly be arbitraged away.

That leads to our third key factor feature—higher risk-adjusted returns must be persistent.

Finally, we believe that there has to be a rationale or intuition behind every factor, even if it’s ultimately close to impossible to prove that this is the reason for its existence. Let us explain. Imagine a strategy that advocated only owning stocks that begin with vowels. We would argue that, even if it had offered meaningful, and even statistically significant alpha, an investor ought to be very wary of a strategy that has no plausible explanation. Mandating that such an explanation...
exists will afford the investor some protection against investing in a strategy that has been lucrative to date, by chance (even tests for statistical significance can’t fully eliminate the role of chance).

That leads to our fourth key factor feature— even meaningful, statistically significant, alpha needs an intuitive economic rationale.

Question three

Are more always merrier—what is the right number of factors?

One of the key differences between factor investing and other types of investing is that factors are not mutually exclusive. With equities, for example, a stock is either German, or French, or Japanese, but never all three. Within sectors, a stock can be in the Information Technology sector, or in the Financial sector, but never in both. So, put simply, a stock’s geographic allocation, and its sector allocation, are completely distinct.

However, this is not true of factors. In the factor world, a stock can exhibit both value and momentum; or it can exhibit quality and low volatility and size. Just because it has one characteristic doesn’t necessarily preclude it from having another (though there are limitations—sometimes one factor is defined as the opposite of another—for example value and growth—and now of course, the ability to belong to both categories is lost).

But the fact that remains that with many factors, which define stocks across suitably different parameters, stocks can have multiple features. Investors can, if they so desire, both have their cake and eat it too (i.e. both have their value and their momentum—eating them is inadvisable).

Given this distinction therefore, here is a suggested three-step framework for determining the “right” number of factors (“right” is in quotation marks because it is ultimately a subjective decision):

- Identify those factors that you believe in, and want exposure to (see the previous section)
- Satisfy yourself that they are complementary (i.e. not philosophical or definitional opposites that might net off, like value and growth) and that there aren’t pairs amongst them that are so highly correlated as to make the inclusion of both unnecessary
- Think hard about the methodology for combining them

We already discussed the first part of this framework in the previous section, and will be going into some detail on methodology (the third consideration) next. So, for now, let’s focus on the un-correlated nature of various factors.

Five well known, empirically—tested, factors with strong heritage are; value, size, momentum, quality and low volatility. To get a sense of how stocks can look across each pair of these factors (ten permutations), we did the following. First, we took the Z-score that FTSE Russell assigned to each stock in the Russell 1000 Index at the end of June. This is just the standardized raw score for each factor, and so lies between –3 and +3 (a process called windsorization forces it to be strictly between these two extremes). Then, we simply produced scatter plots of each pair-wise combination of these scores. The resulting charts are shown in the Appendix.

Two important features stand out. The first is that the relatively uncorrelated nature of most of these pairs of factors is apparent. Indeed, the only pair that has an absolute correlation of greater than 0.50 is momentum and low volatility (and this makes some intuitive sense, a stock that is trending higher is likely to have relatively low volatility). So, it’s probably fair to say that there isn’t really an example of any pair of factors having a correlation so strong that an investor might conclude—if they have one of the factors, then they don’t need the other. We’d argue that each brings something unique to the mix.
The second point is that, generally speaking, there are always quite a large number of stocks in the upper right quadrant of each chart (indeed roughly the 25% you’d expect from a zero correlation). In other words, there are stocks available that exhibit both characteristics, confirming our earlier point about the non-mutually-exclusive nature of factors.

Another way of looking at the question of the right number of factors to consider is that investors ultimately face a trade-off with the number that they include. Too few, though simple, risks leaving strong incremental drivers of equity returns “on the table”. Too many risk additional complexity for the sake of, probably quite rapidly, diminishing marginal excess return.

Question four

How do I combine multiple factors in my portfolio?

So far, we have discussed how to identify factors and offered some thoughts on why seeking exposure to more than one may be desirable. The next question we’d like to address is the methodology by which multiple exposures can actually be achieved in practice.

Broadly speaking, there are two options that are commonly used in the industry—additive (or “composite”) approaches and multiplicative (or “tilt”) approaches. Additive approaches have the virtue of being very simple to understand. An investor just takes a single factor strategy and then blends it with another single factor strategy. So, for example, if they were interested in having exposure to both Value and Momentum, they could allocate half of their assets to each (or, all of their assets to a product that evenly blends the two approaches).

However, because of the fairly uncorrelated nature of many factors, which we discussed in the previous section, this approach runs the risk of diluting factor exposure. It might include stocks that have Value but not Momentum, as well as stocks that have Momentum but not Value (i.e. the upper left and lower right quadrants of the scatter plots in the Appendix).

The alternative approach is to overweight stocks that tend to exhibit both Value and Momentum (and indeed as many other factors as are included in the strategy). Though a little more complicated, this approach has the advantage of more concentrated factor bets. Figures 3 and 4 illustrate this more clearly.

On the y-axis, both charts reflect a 1 out of 5 score each of the stocks in the Russell 1000 received, across five factors—Value, Size, Momentum, Quality and Low Volatility—at the end of June 2016. So, it’s clear that the “worst” stock scored around 0.50 out of 5 and the “best” stock scored around 4 out of 5.

On the x-axis, both charts show the same metric as well—the over, or under, weighting of each stock, relative to its starting market capitalization in the Russell 1000 (so a three on the x-axis, for example, would mean that a stock that had a weight of 0.10% in the Russell 1000 now has a weight of 0.30%).

The only difference between the two charts is the methodology of applying the factor scores. In Figure 3, an additive, or “composite” approach has been used in which each of the stocks has an average of its weightings in each single factor index (which is then rescaled to add up to 100%).

However, in Figure 4, a multiplicative, or “tilt-tilt” approach has been used in which each stock is multiplied by each of its factor scores across the five factors (then re-scaled to add to 100%).

Notice the very powerful result of this straightforward difference in methodology. The additive approach, as one would expect, certainly over weights stocks that score more highly across the five factors. It also under weights those that score below the median (2.5)—but it does so in a relatively conservative manner. Its biggest overweight is 2.2 times the starting market capitalization weight. So, on the stock that it favors the most, the additive approach is prepared to go from, say, 0.10% to 0.22%.

Contrast that to the multiplicative approach. On the exact same stock, the one that has the best combined five
factors score, a tilt approach is prepared to overweight by 26.6 times. So it would take that same initial 0.10% starting weight and move it to 2.6%, a position that is around twelve times the size of the additive approach.

And note that this is broadly true of high-scoring stocks in general. As their scores increase, a multiplicative approach starts to become increasingly aggressive in its conviction (which explains the sharp shift to the right in the plot). Of course, this conviction probably comes at the cost of a higher tracking error, given that the weightings are moving further from market cap on average. And so, as with all investing, one needs to consider that trade-off. Ultimately though, this “conviction level” is a key difference between these methodologies, and investors must, of course, decide which they prefer. (After all, an alpha of 2% and a tracking error of 2% gives the same ratio as an alpha of 5% and a tracking error of 5%, but they are clearly very different investments).

However, we would argue that, if a stock is being evaluated according to its five score factors that have demonstrated their ability to generate alpha, then the far more concentrated approach of the tilt methodology may be preferable over the long run.

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**FIGURE 3: THE RELATIVE WEIGHTINGS ON FIVE FACTOR SCORES FROM AN ADDITIVE, OR “COMPOSITE” APPROACH**

![Graph](Image)

Source: FTSE Russell as of June 2016 rebalance. This chart represents the relative over- or under-weights (compared to the market cap starting universe) that a “composite,” or averaging approach puts on stocks with different factor scores.

**FIGURE 4: THE RELATIVE WEIGHTINGS ON FIVE FACTOR SCORES FROM A MULTIPLICATIVE, OR “TILT” APPROACH**

![Graph](Image)

Source: FTSE Russell as of June 2016 rebalance. This chart represents the relative over- or under-weights (compared to the market cap starting universe) that a “tilt-tilt” or multiplicative approach puts on stocks with different factor scores.
Question five

How to compare multifactor approaches?

In the last section of this paper, we’ll turn to a slightly more technical discussion of our final question—how to compare multifactor strategies. Of course, there are countless different ways of doing this and we won’t claim that the following approach is in any sense exhaustive. But it is certainly worth consideration, and should help to provide insights as investors conduct their due diligence.

The regression approach

For any investor, it’s critical to really put under the microscope the excess returns of a multifactor fund and try to identify the main drivers of those returns. And a good way to do this, specifically, is to regress a fund’s excess returns on the excess returns of a number of single factors to determine two things: whether the factors explain the excess returns and, what those sensitivities look like. An example will help.

Using the same data as we have throughout the paper, we regressed the daily excess returns of the FTSE Russell Comprehensive Factor Index on the excess returns to the five single factors that the index emphasizes—value, size, momentum, low volatility and quality. The results are shown in Figure Five.

There are a few important points to consider: understanding the numbers, interpreting them, and caveating them.

Understanding

First, the r-square. This number provides the proportion of variability in excess return explained by the five factors. Here, that number is 77% which is quite high. It means that the majority of the variability is indeed accounted for by the reasons that you’d hope (overweighting stocks that have these characteristics).

The coefficients to each of the factors are really just “betas” and can be interpreted in the same way that we’d interpret the beta of any single stock—a gauge of sensitivity to another variable. So, just as we’d be used to saying that Stock A’s beta of 1.2 means that if the market is up by 10%, then Stock A would be up by 12%, we can say that the 0.38 beta for Quality means that if the excess return to the Quality factor is 1% then that ought to contribute 0.38% to the excess return on average.

Finally, the standard error, t-statistics and p-values give an idea of the statistical significance of the betas and should not be ignored. Strong betas should have low standard errors, high t-statistics and low p-values. A rule of thumb is that a t-statistic above two means that the beta is significant (i.e. different from zero).

Interpretation

One way to usefully interpret these numbers is to say that, in a good regression model, if you multiply the betas (coefficients) by their respective excess returns, then that should describe the total excess return. So, for example, on a day when each of the five excess returns was 1%, then one would expect the excess return to the multifactor index to be 2.38% (1% * 0.38 + 1% * 0.70 + 1% * 0.17 + 1% * 0.61 + 1% * 0.52). This is the so-called fitted-value. Figure 6 shows a scatter plot of the fitted value for this regression model of the multifactor index against the actual excess returns. One can see that they are very close most of the time.
Caveats

There are a number of intricacies and assumptions within regression analysis that are beyond the scope of this discussion, but we would like to highlight just three critical issues around betas that investors should keep in mind.

First, running this regression on fewer than five factors, instead of all five, will produce a different beta—sometimes very different. And, this makes sense once one remembers that ultimately a regression is answering a very specific research question. An analogy may help here. Suppose you are given the free-throw percentages of a random sample of 1000 people and asked to work out what factors lead to better percentages. You might start by asking for the height of each of the 1000 people, and there’s a good chance you’d find that height was an advantage (i.e. taller people had better percentages). In that instance, you would have a “beta” to height that explained hoop hitting ability. But, overall, the model would be a fairly basic one.

Now suppose that, in addition to height, you were also given each person’s number of years of basketball experience. Now you would have two factors that explained their free throw shooting—height and experience. Clearly, the model has become more sophisticated and, in all likelihood, much better. You could now better explain why some tall people are terrible, and some short people are good (assuming that coaching paid off). A couple of things will almost certainly happen. The r-square will go up, reflecting this richer, more-nuanced model, and the beta to height will change, reflecting the fact that experience is also now being taken into account.

The second caveat, on the topic of changing betas, is that a regression will, rightly, be sensitive to the definition of the explanatory factors. So, returning to our basketball example, you will get different sensitivity to the coaching decision, depending on how you define it. Using “more than 200 hours per year” for example, instead of “more than 50 hours per year” will give different answers. Probably directionally similar, but different. Similarly, investment factors can be defined in different ways and, given that specific funds will use their own specific definitions, they...
will tend to have higher betas to factors defined according to their own criteria, rather than factors defined according to other criteria.

There’s no easy solution to that problem. Using the definitions of a reliable third party system is one option, as is simply regressing on the proprietary definition and being aware of the limitation.

The final caveat is that the absolute beta size, while important, is only half of the story. The likely values of the factor itself are also important. In other words, I should care about my sensitivity to a factor, of course, but I should also care about the excess return to the factor itself. An example will clarify. A fund that has a beta of one to a factor that returns one basis point per year will, on average, have the same pick up to that factor. Clearly, it has a high degree of sensitivity to something that effectively doesn’t matter. Similarly, a fund that has a beta of 0.5 to a factor with an excess return of 10% per year will add 5%. The sensitivity, or beta, has been halved, but the factor now matters.

To round out our basketball analogy, it would be like asking your 1000 players to please specify if they have played in the NBA. The chances are that if they answer yes, then that will have a very powerful impact on their free throw percentage (high beta), but if very few answer yes that is not a great factor to have added to your model.

Conclusions

In this paper we set out to provide some insights around five critical questions that anyone considering factor-based strategies should consider:

**Why should I consider an allocation to these strategies?**
Factor investing arguably sits at the intersection of the Active, Passive and Alternative pillars, and combines many of the best attributes of each.

**How do I identify good factors?**
Apply the four “key factor features” model—higher risk-adjusted returns over the long run that are economically meaningful, persistent, and have intuitive economic rationales.

**How do I decide how many to include?**
Pick factor exposures that you believe in, and be aware of the trade-off between having too few (leaving excess returns on the table), and having too many (complexity). Ensure that your final choices are relatively uncorrelated so that needless factors aren’t included.

**What’s a sound methodology for combining multiple factors?**
There are many of them. Be sure to understand the process fully and know the relative pros and cons of your chosen methodology.

**How can I compare various multifactor approaches?**
Start by regressing the multifactor excess returns on the single factor excess returns, but be aware of the subtleties around this approach.
Appendix

Pair-wise Scatter plots for Z-scores on value, size, momentum, quality and low volatility for the Russell 1000 stocks as at 6/27/16 (Source: FTSE Russell)

Past performance is not indicative of future results.

Source: DWS as of December 2016.

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Gimme five—five key questions for factor investors

February 2019

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**Definition of terms**

Alpha—The excess risk-adjusted return of a fund relative to the return of a benchmark index.

Beta measures a security's sensitivity to the movements of the fund’s benchmark or the market as a whole. A beta of greater than one indicates more volatility than the benchmark or market, while a beta of less than one indicates less volatility.

Correlation is a measure of how closely two variables move together over time. A 1.0 equals perfect correlation.

A –1.0 equals total negative correlation.

R-squared is a statistic that indicates how closely a fund’s performance correlates to the performance of a benchmark.

Sharpe ratio measures an investment’s performance per unit of risk for a given period.

T-statistic is used to test hypotheses. It is a ratio of the departure of an estimated parameter from its notional value (total value of a leveraged position’s assets) and its standard deviation (volatility).

**Index definitions**

The Russell 1000 Index tracks the performance of the 1,000 largest stocks in the Russell 3000 Index, which consists of the 3,000 largest U.S. companies as measured by market capitalization. It is not possible to invest directly in an index.

The FTSE Russell 1000 Comprehensive Factor Index is a benchmark designed to capture exposure to five factors—Quality, Value, Momentum, Low Volatility and Size. These factors represent common factor characteristics for which there is a broad academic and practitioner consensus, supported by a body of empirical evidence across different geographies and time.

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