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The Risks of Deviating from Academically-Validated Factors

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Abstract

Factor investing has never been as popular as it is today. However, with the propagation of this type of investment approach, the equity space is becoming increasingly saturated with more and more factors that are ever more removed from academically-grounded research. In a bid to maintain their apparent competitive advantage and to show that they are still delivering alpha, commercial index providers and asset managers have respectively embarked on a factor finding process that has resulted in the discovery of tens, hundreds or even thousands of factors. However, proprietary factor definitions and analytic toolkits produce non-standard factors, and this can lead to unintended exposures and misunderstandings surrounding the associated risk exposures. The further away they are from academically-validated research, the more spurious and redundant proprietary factor definitions may be. Investors can choose to rely on standard factors that have survived the scrutiny of countless empirical studies and have been independently replicated and validated. Alternatively, they can choose to forego this free due diligence and take on the risk of selecting a provider-specific factor definition, which is somewhat similar to taking on the risk of selecting an active manager. Scientific Beta's research is underpinned by academic principles and aims to remind the investment community of the original promise of factor investing.

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The Promise of Factor Investing

The Promise of Factor Investing

Factor investing offers a big promise. By identifying the persistent drivers of long-term returns in their portfolios, investors can understand which risks they are exposed to, and make explicit choices about these exposures. This idea has gained popularity among long-term investors ever since the publication in 2009 of an influential report by finance professors on the performance of the Norwegian sovereign fund (Ang et al., 2009).

An often-cited analogy is to see factors as the "nutrients" of investing. Just like information on the nutrients in food products is relevant to consumers, information on the factor exposures of investment products is relevant to investors. This analogy also suggests that factors cannot be arbitrary constructs. What would you think if Nestlé used its own definition of "saturated fat" for the information on its chocolate packets and if McDonald's also had its own, but different, definition for the content of its burgers? Further, would it not be curious if both definitions had nothing to do with the definition that nutritionists and medical researchers use?

When it comes to information about factors, however, this is exactly the situation that we find. Investment products that aim to capture factor premia have gained popularity. Furthermore, investors rely heavily on analytic toolkits to identify factor exposures of an investor's portfolio. However, neither investment products nor analytic tools necessarily follow the standard factor definitions that peer-reviewed research in financial economics has established.

Investors benefit from understanding and controlling their exposure to factors, only if these factors are reliable drivers of long-term returns. Factor definitions that have survived the scrutiny of hundreds of empirical studies and have been independently replicated in a large number of data sets are of course more reliable than ad-hoc constructs used for the specific purposes of a product provider.

Perhaps more importantly, the process by which factors are defined in practice is inherently flawed. Common practices in designing these factors increase the risk of retaining factors that will ultimately be irrelevant as drivers of long-term returns.

This paper will discuss factor definitions used in investment products and analytic tools offered to investors and contrast them with the standard academic factors. We also outline why the methodologies used in practice pose a high risk of ending up with irrelevant factors.

Are Factors Grounded in Academic Research?

Are Factors Grounded in Academic Research?

Factor models link returns of any investment strategy to a set of common factors. In addition to the market factor, commonly used factors include size, value, momentum, profitability and investment, which capture the difference of returns across firms with different characteristics. In financial economic research, a small number of models have become workhorses for analysing asset returns and fund manager performance, given the consensual understanding that they contain the factors that matter for asset returns. Providers of factor-based investment tools and strategies unequivocally claim that their factors are "grounded in academic research".[1] However, we will show that the factors used are instead completely inconsistent with the factors that are supported by a broad academic consensus.

5 or 500 factors?

Exhibit 1 provides an overview of the workhorse models in academic finance. There are three obvious insights:

- Different models use identical factor definitions;
- The number of factors is limited to about a handful of factors;
- Factors are defined by a single variable.

These three properties ultimately mean that the different factor models draw on very few variables, which have been identified as persistent drivers of long-term returns.

Exhibit 1: Factor Definitions in Equity Factor Models that are Predominant in the Academic Literature on Mutual Fund Performance Evaluation and Asset Pricing

<table>
<tr><th rowspan="2"></th><th colspan="5">Factor Definitions for</th><th colspan="2">Number</th></tr>
<tr><th>Size</th><th>Value</th><th>Momentum</th><th>Profitability</th><th>Investment</th><th>of non-market factors</th><th>of variables per factor</th></tr>
<tr><td>Fama, French (1993)</td><td rowspan="5">Market Cap</td><td rowspan="4">Book/ Market</td><td></td><td></td><td></td><td>2</td><td>1</td></tr>
<tr><td>Carhart (1997)</td><td rowspan="2">Past returns</td><td></td><td></td><td>3</td><td>1</td></tr>
<tr><td>Chordia, Goyal, Saretto (2017)</td><td rowspan="2">Gross Profit / Book Equity</td><td rowspan="3">Asset Growth</td><td>5</td><td>1</td></tr>
<tr><td>Fama, French (2015)</td><td></td><td>4</td><td>1</td></tr>
<tr><td>Hou, Xue, Zhang (2015)</td><td></td><td></td><td>Profit / Book Equity</td><td>3</td><td>1</td></tr>
</table>

In contrast, the factor tools from commercial providers typically include a proliferation of variables. MSCI's "Factor Box" draws on 41 different variables to capture the factor exposures of a given portfolio.[2] S&P markets a "Factor Library" which, despite including more than 500 variables[3] "encompassing millions of backtests," wants to help you "simplify your factor investing process". BlackRock proudly announces "thousands of factors" for its Aladdin Risk tool.[4]

This raises the question of why the standard models avoid such a proliferation of variables. First, the need for more factors is often rejected on empirical grounds. For example, Hanna and Ready (2005) show that using 71 factors does not add value over a model with two simple factors (book-to-market and momentum). Similarly, Hou, Xue and Zhang (2015) show that a model with four

1 - See "Foundations of Factor Investing", MSCI Research Insight (December 2013).
2 - See MSCI (2017): "Use of the Global Equity Model (GEM LT) In MSCI Index Construction" , available at <https://bit.ly/2x2EhOx>
3 - See <https://bit.ly/2OdIhTS>
4 - See <https://bit.ly/2x8D8Vz>

Are Factors Grounded in Academic Research?

simple factors does a good job at capturing the returns across a set of nearly 80 factors. Second, academic research limits the number and complexity of factors because a parsimonious description of the return patterns is likely to be more robust. Increasing the number of variables will obviously improve fitting the model to a given data set but will also reduce the robustness when applying model results beyond the dataset of the initial tests. These two points are analysed in more detail later in the paper.

Non-Rewarded versus Rewarded Factors

Non-Rewarded versus Rewarded Factors

Before we proceed, it is necessary to clarify a common source of confusion. Several definitions of the term "factors" exist, with some of them focused on the variability in returns (i.e. short term fluctuations) and others on the expected returns of assets (i.e. long term average returns). Martellini and Milhau (2018) provide a taxonomy of factors that distinguishes between these different definitions and their uses. A first type of factors can be used to describe common sources of risk across assets. In this setting, volatilities and correlations among the assets are driven by exposures to a certain set of factors. While this information can provide some understanding of the fluctuations in a portfolio, it does not explain what the driver of long-term returns is. Such factors are referred to as non-rewarded factors. Naturally, there are a number of such non-rewarded factors that can help capture short-term fluctuations. For example, short-term fluctuations of an equity portfolio may be explained by its sector exposures, its country exposures, exposures to currency or commodity risks, among many other possibilities. However, since such factors are not rewarded, an investor does not gain additional returns from such exposures.

Rewarded factors are factors that explain differences in the long-term expected return in the cross-section of the assets. From an allocation point of view, knowledge about these factors enables an investor to tilt a portfolio towards stocks with high exposure to a factor that is positively rewarded. This results in a higher long-term expected return for the portfolio. Investors need to be cautious to avoid misinterpreting a factor offered in commercial factor tools as rewarded, when it is actually not. Dividend yield, for example, is included in the factor model of MSCI because it is a source of "time-varying return and risk".[5] However, it does not explain cross-sectional differences in the long-term expected return (Hou et al., 2015).

Exhibit 2 provides an illustration to explain this distinction further. Suppose an investor in an equal-weighted equity index wants to understand the implicit sector bets he makes. For this purpose, he is interested in the portfolio's exposure to an industry factor that is proxied by the performance difference between technology and utility stocks. While this analysis can provide information about the way the portfolio return varies with the differences in sector performance, it will not necessarily explain the long-term returns of the portfolio.

The first row of the table shows the results of a regression of the excess returns of the equal-weighted index on the industry factor. The p-value of zero indicates that the exposure is highly significant. The R^2 suggests that the industry factor explains around 20% of the variance in portfolio returns. Therefore, in terms of understanding the short-term variability in returns, this analysis can be useful. The bottom row of the table, however, shows that the factor does not exhibit a long-term return that is significantly different from 0. Exposure to this factor will thus not be useful to understand the long-term return drivers of the portfolio. Furthermore, tilting the portfolio towards stocks with a high exposure to this factor will not result in a higher expected return. The idea of factor investing is to tilt a portfolio towards a rewarded risk factor. Without a long-term premium, there would be no reason to take on the factor's risk.

5 - See "Best practices in factor research and factor models" MSCI Research Insight (November 2018), available at <https://www.msci.com/www/research-paper/best-practices-in-factor/01163021280>

Non-Rewarded versus Rewarded Factors

Exhibit 2: Risk and Return Influence of the Technology Minus Utilities Factor (TMU) on an Equal-Weighted Portfolio
The top row of the table shows the regression results of the excess returns of the equal-weighted portfolio over the risk-free rate on the TMU factor. The bottom row shows the long-term performance of the TMU factor. The analysis is based on daily total returns for the period 19-Jun-1970 to 29-Dec-2017. The stock universe consists of the 500 largest US stocks. The equal-weighted portfolio is represented by the EDHEC-Risk Long-Term United States Maximum Deconcentration Index. The TMU factor returns are calculated as the returns on the cap-weighted portfolio of the technology stocks in the universe minus the returns on the cap-weighted portfolio of the utility stocks in the universe. The secondary market US Treasury Bills (3M) is the risk-free rate.

Regression results	Coefficient	P-value	R^2
Explaining short-term fluctuations	0.32	0.00	0.19
Long-term returns	**Ann. Return**	**P-value**	
Factor premium (long-term average return)	-0.97%	0.65	

Spurious Factors

Spurious Factors

A severe problem with commercially used factors is the process by which they are defined. This process increases the risk of falsely identifying factors, due to weaknesses in the statistical analysis. In fact, providers will analyse a large set of candidate variables to define their factors. Given today's computing power and the large number of variables representing different firm characteristics, such an exercise makes it easy to find so-called "factors" that work in the given dataset. However, these factors most likely will have no actual relevance outside the original dataset. That data-mining will lead to the identification of false factors is a problem that is well known to financial economists. Lo and MacKinlay (1990) provided an early warning against careless analysis: "[…] the more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge."

Selection Bias

It is well known that simply seeking out factors in the data without a concern for robustness will lead to the discovery of spurious factors. This is due to a "selection bias" of choosing among a multitude of possible variables. Harvey et al. (2016) document a total of 314 factors with positive historical risk premia showing that the discovery of the premium could be a result of data-mining (i.e. strong and statistically-significant factor premia may be a result of many researchers searching through the same dataset to find publishable results). The practice of identifying merely empirical factors is known as "factor fishing" (see Cochrane, 2001). Therefore, a key requirement for investors to accept factors as relevant in their investment process is that there be clear economic rationale as to why the exposure to this factor constitutes a systematic risk that requires a reward, and why it is likely to continue producing a positive risk premium (Kogan and Tian, 2013). In short, factors selected on the sole basis of past performance without considering any theoretical evidence are not robust and must not be expected to deliver similar premia in the future. This is emphasised by Harvey (2017), who argues that "economic plausibility must be part of the inference".

In addition, there are statistical tools to adjust results for the biases arising from testing a large number of variables. A recent study (Chordia et al. (2017)) also emphasises the factor-fishing problem. They show that it is easy to find great new factors in backtests but such factors add no real value to standard factors. They create more than two million factors (levels, growth rates, and ratios) from 156 accounting variables and assess whether these factors generate performance. While they find that there are 22,337 (!) great factors, the winning ratios do not make any economic sense (such as the ratio of Common Stock minus Retained Earnings to Advertising Expense). Moreover, these factors do not survive more careful vetting. None of the 20,000+ factors that appear significant survives after adjusting for the well-known standard factors (size, value, momentum, profitability, investment and market) and for selection bias. These results emphasise that it is easy to discover new factors in the data if enough fishing is done, but such factors are neither economically meaningful nor statistically robust.

Of course, exposure to non-robust factors with an unreliable backtest performance will not prove useful to an investor going forward. The past will give an inflated picture of the factor-based performance that can be expected for the future.

Spurious Factors

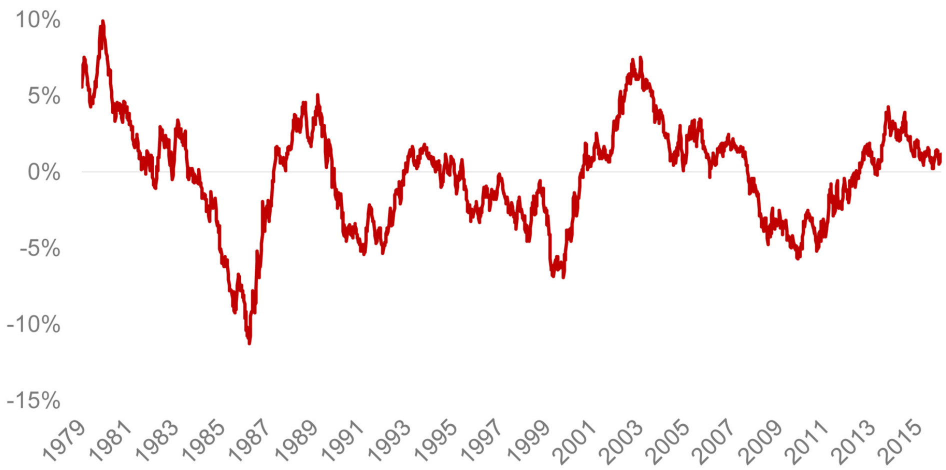
Composite Scores

In the discussion thus far, we emphasised that a stark problem arises from a practice where providers of factor tools select flexibly from among many variables. It turns out that the actual problem is even worse in practice. Providers of factor products and tools do not stop their data-mining practices at the level of selecting single variables. Instead, they create complex composite factor definitions drawing on combinations of variables.

Research by Novy-Marx (2015) shows that the use of composite variables in the definition of factors yields a "particular pernicious form of data-snooping bias", the overfitting bias. Intuitively, this bias arises because, in addition to screening the data for the best-performing variables, combining variables that give good backtest results provides even more flexibility to seek out spurious patterns in the data. The author concludes that "combining signals that backtest positively can yield impressive back-tested results, even when none of the signals employed to construct the composite signal has real power".

When combining variables to improve back-tested factor performance, providers can yet again increase flexibility for capturing spurious patterns in the data. Additional flexibility is easily achieved by attributing arbitrary weightings to the variables used in a composite definition. For a given combination of variables, changing the weight each variable receives in the factor definition may have a dramatic impact on factor returns. Exhibit 3 illustrates this point. The graph plots return differences over three-year horizons of two factor-tilted portfolios that draw on the same three variables to define a quality score. The only difference between the quality factor definitions is the weighting of the three component variables (profitability, leverage and investment). The difference in weightings used in the composite factor definitions leads to return differences that often exceed 5% annualised. Such pronounced differences suggest that, in a given sample, it is easy to improve factor returns by specifying arbitrary weightings for composite factor definitions.

Exhibit 3: Difference Between Annualised 3-Year Rolling Returns of Two "Quality" Portfolios Using Different Weightings on the Same Set of Variables. The weights in the two portfolios are as follows. Portfolio 1: Inv. 30%, Prof. 60%, Lev. 10%, Portfolio 2: Inv. 60%, Prof. 30%, Lev. 10%. Analysis is based on daily total returns in USD, from 31-Dec-1976 to 31-Dec-2016. The plotted line corresponds to the difference between three-year rolling annualised returns of the two 'Quality' portfolios. Portfolios were formed by selecting stocks with the top 10% composite score and equal weighting them. The composite scores were defined by investment, profitability and leverage scores, weighted in two different ways: 60-30-10 and 30-60-10 respectively. The composite scores are standardised using cap-weighted mean and unit standard deviation.



Spurious Factors

What Do Providers Do?

Given the well-documented risk of biases leading to useless factors, providers of factor products should use the Academically-Validated factor definitions. Indeed, many providers claim that their factors are grounded in academic research. MSCI, for example, recently issued a report that clearly emphasises this.[6] They state that their "factor research is firmly grounded in academic theory and empirical practice". FTSE also mentions the broad academic consensus that exists for the factors used in their global factor index series.[7]

It is important to highlight, however, what having a strong academic foundation should mean. To claim that a specific factor is "firmly grounded" in academic research means that it should fulfil two criteria. First, its existence should be replicated and documented across different independent studies. This gives investors the assurance that the methodologies are externally validated and that the factors also exist outside of the original data set. Second, a risk-based explanation should support the existence of the factor. Without this, there is no reason to expect the persistence of the factor performance. Post-publication evidence is needed to confirm that the factor does not disappear after it is published. To support a claim for academically grounded factors, providers should be able to list the independent studies showing that these two requirements are fulfilled.

This does not mean that using new or proprietary factors will necessarily fail out of sample. However, the problem is that it is not possible to obtain the same assurances for the effectiveness of the factor compared to academically grounded factors. Hou et al. (2018) show that the majority of anomalies in financial research cannot be replicated. This means that there is no reason to assume that they will be useful for an investor going forward. A prudent approach is thus to only select factors that have indeed been independently replicated. With this in mind, why would one rely on provider specific research concerning a new factor when you have free due diligence from the academic community concerning a standard set of factors? Consequently, it is clear that the use of proprietary factors exposes an investor to risks that can easily be avoided.

Whereas the factor names are usually based on factors that are presented in the literature, the actual implementation of most product providers is very different. Exhibit 4 gives some examples of variable definitions being used by different index providers as a proxy for the factors. These can be compared to the definitions academics use for the factors, as displayed in Exhibit 1 earlier. It is clear that provider definitions are more complex than academic factor definitions and differ substantially from the externally validated factors despite using the same factor labels, such as "value" and "momentum". A relevant question for investors is whether the "upgraded" definitions of standard factors, like "enhanced value" and "fresh momentum" add value only in the backtest or whether the benefits hold post publication (i.e. in a live setting). Moreover, in the absence of external replication of such factors, investors are fully reliant on provider-specific results.

6 - See "Best practices in factor research and factor models" MSCI Research Insight (November 2018), available at <https://www.msci.com/www/research-paper/best-practices-in-factor/01163021280>
7 - See <https://www.ftse.com/products/indices/factor>

Spurious Factors

Exhibit 4: Examples of variable definitions used by index providers[8]

Factor	FTSE	MSCI	S&P	RAFI
Size	Log of full market cap	Equal-weighted	-	Equal weight of small universe portfolios of value, low volatility, quality and momentum
Value	Composite of cash flow yield, earnings yield and country relative sales-to-price ratio	Composite of forward price-to-earnings, price-to-book and enterprise value-to-operating cash flow	Composite of book value-to-price, earnings-to-price and sales-to-price	Ratio of fundamentals to capitalization weight
Momentum	Cumulative 11 month returns	Combination of 6 and 12 month risk-adjusted excess return	12 month risk-adjusted price change excluding the most recent month	Combination of standard momentum, idiosyncratic momentum and fresh momentum
Quality	Composite of profitability, efficiency, earnings quality and leverage	Composite of ROE, debt-to-equity and earnings variability	Composite of ROE, accruals ratio and financial leverage ratio	Combination of high profitability and low investment

The exhibit also shows that many providers use composite scores in their factor definitions. As discussed above, this opens the door for an overfitting bias, even if composites are equal-weighted across constituent variables. Providers add even more flexibility to their factor definitions by making decisions on how to weigh the different variables within the composite. For example, one provider uses an approach involving "intuition […], investors' expectations or other measures"[9] to attribute weights when combining variables into composites.[10] Another provider uses a statistical procedure to weight variables making up a composite factor.[11]

Overall, product providers explicitly acknowledge that the guiding principle behind factor definitions is to analyse a large number of possible combinations in short data sets and then retain the factors that deliver the highest backtest performance. In fact, providers' product descriptions often read like a classical description of a data-snooping exercise, which is expected to lead to spurious results. For example, one provider states[12] that, when choosing among factor definitions, "adjustments could stem from examining factor volatilities, t-stats, Information Ratios", with an "emphasis on factor returns and Information Ratios". Another provider states that "factors are selected on the basis of the most significant t-stat values", which corresponds to the technical definition of a procedure that maximises selection bias.[13]

Despite a lack of empirical or economic grounding, factor definitions used by providers may appear to be advantageous in practice. This is the case notably when index providers offer both analytics tools and indices, and ensure that factor definitions in their indices correspond to those used in their tools. If an analytics tool and a set of indices are based on the same factor definitions, the indices will show an exposure to the factors by construction. Other investment strategies may be more difficult to explain by the proprietary factor definitions of the provider and thus appear more difficult to interpret to investors. However, if the factors are flawed to start with, such correspondence of course does not add any real value to investors.

8 - These definitions are taken from: <https://www.ftse.com/products/downloads/FTSE_Global_Factor_Index_Series_Methodology_Overview.pdf>, <https://www.msci.com/factor-indexes>, <https://us.spindices.com/index-finder/> and <https://www.researchaffiliates.com/en_us/strategies/rafi/rafi-multi-factor.html>
9 - See MSCI (2018), Introducing MSCI FaCS, available at <https://www.msci.com/documents/10199/d923cc18-6493-4245-9707-56e9b6609528>
10 - It is further stated in a different publication that "equal weights are used unless there are compelling reasons to deviate from them", see "Best practices in factor research and factor models" MSCI Research Insight (November 2018) available at <https://www.msci.com/www/research-paper/best-practices-in-factor/01163021280>. Of course, if one wanted to limit flexibility it would be necessary to state stronger constraints than a broad reference to requiring "compelling reasons" for deviation.
11 - See Sousa Costa and Marques Mendes (2016), available at: <https://bit.ly/2p1mnbd>
12 - See MSCI (2018), Introducing MSCI FaCS, available at <https://www.msci.com/documents/10199/d923cc18-6493-4245-9707-56e9b6609528>
13 - See FTSE (2014), "Factor exposure indexes - Value factor", available at <https://www.ftserussell.com/sites/default/files/research/factor_exposure_indexes-value_factor_final.pdf>

Redundant Factors

Redundant Factors

For many factors used in investment practice, it is well known that they fail to deliver a significant premium. For example, different analytics packages[14] include the dividend yield, leverage, and sales growth as factors, while all of these factors have been shown not to deliver a significant premium (for the Dividend Yield, see Hou et al., 2015, for leverage see Kyosev et al., 2016, for growth see Lakonishok et al., 1994).

Factors may also be redundant with respect to consensual factors from the academic literature. In fact, many proprietary factors may have return effects, which can be explained away by the fact that they have exposures to standard factors (see Fama and French, 1996). We can illustrate this point by analysing the popular dividend yield factor.

Exhibit 5: The Premium for Dividend Yield is Insignificant
Analysis is based on monthly total returns in USD for the period 30-Jun-1927 to 31-Dec-2016. All the data comes from the K. French data library. Numbers that are statistically significant (p-value less than 5%) are formatted in bold.

	Portfolios Sorted by Dividend Yield					
US Long-Term	Low (Q1)	Quintile 2	Quintile 3	Quintile 4	High (Q5)	Q5 - Q1
Average Return	0.90%	0.94%	0.92%	1.08%	1.04%	0.14%
t-stat	-	-	-	-	-	1.07
CAPM Model						
Unexplained	-0.05%	0.05%	0.04%	**0.21%**	0.14%	-0.09%
Market Exposure	**1.05**	**0.94**	**0.94**	**0.93**	**0.97**	-0.08
R-squared	91.07%	92.24%	89.32%	86.50%	75.58%	0.93%
Fama-French 3-Factor Model						
Unexplained	0.02%	0.08%	0.01%	**0.14%**	-0.01%	**-0.31%**
Market Exposure	**1.09**	**0.98**	**0.95**	**0.91**	**0.89**	**-0.20**
Size (SMB)	**-0.04**	**-0.14**	**-0.15**	**-0.13**	-0.04	0.01
Value (HML)	**-0.22**	**-0.05**	**0.15**	**0.25**	**0.54**	**0.76**
R-squared	92.79%	93.08%	90.87%	89.53%	85.02%	38.04%

Exhibit 5 shows that the dividend yield factor does not lead to significant returns. Moreover, when adjusting returns for the exposure to the standard value (book-to-market) effect, the dividend yield factor actually delivers negative returns.

Popular factor products and tools contain a large number of factors that do not deliver an independent long-term premium. This is bad news for investors who are using such tools to understand the long-term return drivers of their portfolios.

14 - See for example Style Analytics (2018), available at https://bit.ly/2Nznq04.

Getting Your Exposures Wrong

Getting Your Exposures Wrong

Below, we will illustrate the risks of using non-standard factors. We will look at the results of a set of regressions of the excess returns of two composite quality factor indices over a broad cap-weighted index[15] on the returns of academically-grounded and widely-accepted factors, including the quality-related factors of profitability and investment. This will allow us to assess the exposures of the quality indices to the academic factors and show that there is a clear mismatch between the intended and achieved exposures. As the quality factor indices, we use the MSCI World Quality Index (MQI) and the FTSE Developed Quality Factor Index (FQI). The former "aims to capture the performance of quality growth stocks by identifying stocks with high quality scores based on three main fundamental variables: high return on equity (ROE), stable year-over-year earnings growth and low financial leverage".[16] The latter defines quality as a "composite of profitability, efficiency, earnings quality and leverage"[17]. The data on the regressors are taken from the data library of Kenneth French, where we use the 5-factor model, including a market, size, value, profitability and investment factor, together with the momentum factor.[18] Contrary to the quality definition used in the quality indices, these factors are part of standard multi factor asset pricing models that are extensively used and scrutinised in the academic literature, have a considerable post-publication record, and have been explained as compensation for risk.

Exhibit 6: Exposure of Composite Quality Factor Indices excess returns to Standard Factors
Analysis is based on weekly return data for the period starting on 20 June 2002 and ending on 30 June 2018, for which we have data for both indices. The first two columns of each panel show the regression betas together with their t-statistic. The third column shows how much of the annualised excess return of the index can be attributed to the different regressors based on their average returns and their exposures. The last column shows the relative size of the impact each of the factors had on the index excess returns, calculated as the absolute value of its performance attribution divided by the sum of the absolute values of the performance attributions.

Panel A: MSCI World Quality Index results

MSCI World Quality Index	Exposure (beta)	t-stat	Performance Attribution	Impact on Performance
Ann. alpha	0.01	1.75	0.96%	30.04%
Market	-0.06	-8.82	-0.47%	14.65%
Size	-0.20	-12.15	-0.29%	9.18%
Value	-0.26	-13.49	-0.31%	9.69%
Momentum	0.04	4.79	0.15%	4.64%
Profitability	0.39	15.01	1.01%	31.67%
Investment	0.00	-0.14	0.00%	0.12%
R^2	64.06%	Total	1.04%	100.00%

Panel B: FTSE Developed Quality Factor Index results

FTSE Developed Quality Factor Index	Exposure (beta)	t-stat	Performance Attribution	Impact on Performance
Ann. alpha	0.00	0.52	0.18%	10.86%
Market	-0.02	-5.31	-0.17%	10.26%
Size	0.02	1.76	0.03%	1.54%
Value	-0.19	-16.07	-0.22%	13.43%
Momentum	0.05	9.85	0.18%	11.11%
Profitability	0.27	17.80	0.72%	43.69%
Investment	0.15	9.02	0.15%	9.12%
R^2	71.32%	Total	0.86%	100.00%

15 - We use the MSCI World Index as the broad cap-weighted index.
16 - See <https://www.msci.com/documents/10199/344aa133-d8fa-4a15-b091-20a8fd024b65>
17 - See <https://www.ftse.com/products/downloads/FTSE_Global_Factor_Index_Series_Methodology_Overview.pdf>
18 - See <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html>

Getting Your Exposures Wrong

Panel A of Exhibit 6 shows the results for the MQI and Panel B shows the results for the FQI. The first observation from these results is that the t-statistics point to a significant exposure to all the different factors, except from the investment factor in the MQI case and the size factor in the FQI case. As would be expected for a quality index, the exposures to profitability are the most clear with betas of 0.39 and 0.27.

However, for the MQI, the exposures to the market, size and value factors are also sizeable, but negative, with betas of -0.06, -0.20 and -0.26, respectively. For the FQI, we obtain similar results with a significantly negative beta of -0.02 and -0.19 for the market and value factors, respectively. Obtaining strong negative exposures to factors that are unrelated to quality is an important, presumably unintended, consequence of investing in these quality indices. Apart from the market exposure for the FQI, these exposures are also larger in absolute value than the respective exposures to the investment factor, which would be expected to show a relatively stronger influence on a quality index. Instead, the investment exposure is estimated to be zero for the MQI. Clearly, the composite quality indices expose an investor to a range of standard factors other than the quality-related profitability and investment factors.

When we look at the contribution of the different factors to the average annualised excess return of the indices over the period, we see that for the two quality indices, only 31.79% and 52.81% respectively of the impact on the excess returns comes from the quality-related factors profitability and investment. A large part of excess returns can be attributed to other standard factors or are unrelated to any factors. In fact, a big part of performance (30.04%) remains unexplained by any of the standard factors in the case of the MQI.

Taken together, these results show that the composite quality indices are only moderately related to the academic profitability and investment factors, while a large part of their performance is either driven by other factors such as the market, or remain unexplained by the set of standard factors used in the model. An investor in these indices will thus expose him- or herself to a large amount of unintended risk factors unrelated to quality.

This risk is present in any index based on non-standard factor definitions. Proprietary factor definitions lead to a risk of misunderstanding factor exposures.

Conclusion: Reviving the Promise of Factor Investing

Conclusion: Reviving the Promise of Factor Investing

Factors used in investment practice show a stark mismatch with factors that have been documented by financial economists. Commercial factors are based on complex composite definitions that offer maximum flexibility. Providers use this flexibility to seek out the factors with the highest performance in a given dataset. Such practice allows spurious factors to be found. Spurious factors work well in a small dataset but will be useless in reality. Therefore, many factors that appear in popular investment products and analytic tools are likely false.

Even though many providers claim their factors are grounded in academic research, we have emphasised that two important conditions to support this claim are often not fulfilled. The factor definitions should have been used and validated across different independent studies and a risk-based explanation should support the existence of the factor. Without these assurances, there is no reason to assume the persistence of the factor.

We have also shown that relying on proprietary factor definitions can lead to unintended exposures. For example, investors who tilt towards a composite quality factor will end up with a strategy where, depending on the index we consider, only about one third or half of the excess returns are driven by exposure to the two well-documented quality factors (profitability and investment). This means that the part of the excess returns that is unrelated to quality factors can be as high as two-thirds, an obvious misalignment with the explicit choice to be exposed to quality factors (see Exhibit 6). Even if the quality factors perform as expected by the investor, this performance will not necessarily be reflected in portfolio returns, which are in a large part driven by other factors and idiosyncratic risks.

Available factor products thus do not deliver on the promise of factor investing, described almost a decade ago in the Norway study. Understanding the factor drivers of returns increases transparency and allows investors to formulate more explicit investment choices. However, being aware of exposures to useless factors, which have no reliable link with long-term returns, is equally useless.

A good idea can easily be distorted when implemented with poor tools. For a meaningful contribution to the ability of investors to make explicit investment choices, factor investing should focus on persistent and externally-validated factors. It is time to recall the good idea of factor investing.

References

References

- Ang, A., W. Goetzmann and S. Schaefer. 2009. Evaluation of Active Management of the Norwegian Government Pension Fund - Global.
- Bender, J., R. Briand, D. Melas and R.A. Subramanian. 2013. Foundations of Factor Investing, MSCI Research Insight (December).
- Carhart, M. 1997. On Persistence of Mutual Fund Performance. *Journal of Finance* 52(1): 57–82.
- Chordia, T., A. Goyal and A. Saretto. 2017. p-Hacking: Evidence from Two Million Trading Strategies. Swiss Finance Institute Research Paper No. 17-37.
- Cochrane, J. 2001. Asset Pricing. Princeton, NJ: Princeton University Press.
- Fama, E.F. and K.R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33(1): 3-56.
- Fama, E. and K.F. French. 1996. Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* 51(1): 55-84.
- Fama, E.F. and K.R. French. 2015. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1): 1-22.
- FTSE Russell. 2014. Factor exposure indexes - Value factor. Available at <https://www.ftserussell.com/sites/default/files/research/factor_exposure_indexes-value_factor_final.pdf>.
- Hanna, J. D. and M. J. Ready. 2005. Profitable Predictability in the Cross Section of Stock Returns. *Journal of Financial Economics* 78(3): 463-505.
- Harvey, C. 2017. Presidential Address: The Scientific Outlook in Financial Economics. *Journal of Finance* 72(4): 1399-1440.
- Harvey, C., Y. Liu and H. Zhu. 2016.… and the Cross-Section of Expected Returns. *Review of Financial Studies* 29 (1): 5-68.
- Hou, K., C. Xue and L. Zhang. 2015. Digesting Anomalies: An Investment Approach. *Review of Financial Studies* 28(3): 650–705.
- Hou, K., C. Xue and L. Zhang. 2018. Replicating Anomalies. The Review of Financial Studies. Forthcoming.
- Kogan, L. and M. Tian. 2013. Firm Characteristics and Empirical Factor Models: A Data-Mining Experiment. MIT Working Paper.
- Kyosev, G., M.X. Hanauer, J. Huij and S. Lansdorp. 2016. Quality Investing – Industry versus Academic Definitions. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2794807 (13 June).
- Lakonishok, J., A. Shleifer and R.W. Vishny. 1994. Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49(5): 1541-1578.
- Lo, A.W. and C. MacKinlay. 1990. Data Snooping biases in Tests of Financial Asset Pricing Models. *Review of Financial Studies* 3(3): 431-467.
- Martellini, L. and V. Milhau. 2018. Smart Beta and Beyond: Maximising the Benefits of Factor Investing. EDHEC-Risk Institute Publication (February).
- Melas, D. 2018. Best Practices in Factor Research and Factor Models, MSCI Research Insight (November).
- MSCI. 2017. Use of the Global Equity Model (GEM LT) In MSCI Index Construction. MSCI Presentation, available at https://bit.ly/2x2EhOx. (January).

References

- MSCI. 2018. Introducing MSCI FaCS – A New Factor Classification Standard for Equity Portfolios (January).
- Novy-Marx, R. 2015. Backtesting Strategies Based on Multiple Signals. Working Paper. National Bureau of Economic Research.
- Sousa Costa, R. and M. Marques Mendes. 2016. Understanding Multi-Asset Factor Models. Nova School of Business and Economics, Presentation available at: < https://bit.ly/2p1mnbd>.

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About Scientific Beta

EDHEC-Risk Institute set up Scientific Beta in December 2012 as part of its policy of transferring know-how to the industry. Scientific Beta is an original initiative which aims to favour the adoption of the latest advances in "smart beta" design and implementation by the whole investment industry. Its academic origin provides the foundation for its strategy: offer, in the best economic conditions possible, the smart beta solutions that are most proven scientifically with full transparency of both the methods and the associated risks. Smart beta is an approach that deviates from the default solution for indexing or benchmarking of using market capitalisation as the sole criterion for weighting and constituent selection.

Scientific Beta considers that new forms of indices represent a major opportunity to put into practice the results of the considerable research efforts conducted over the last 30 years on portfolio construction. Although these new benchmarks may constitute better investment references than poorly-diversified cap-weighted indices, they nevertheless expose investors to new systematic and specific risk factors related to the portfolio construction model selected.

Consistent with a full control of the risks of investment in smart beta benchmarks, Scientific Beta not only provides exhaustive information on the construction methods of these new benchmarks but also enables investors to conduct the most advanced analyses of the risks of the indices in the best possible economic conditions.

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2018 Publications

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• Aguet, D., N. Amenc, F. Goltz and A. Lodh. How to Harvest Factor Premia without Suffering from Market Volatility: The Case for a Long/Short Multi-Factor Strategy (October).

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• Lodh, A. and S. Sivasubramanian. Scientific Beta Diversified Multi-Strategy Index. (June).

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• Gautam, K., A. Lodh, and S. Sivasubramanian. Scientific Beta Efficient Maximum Sharpe Ratio Indices. (May).

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• Sivasubramanian, S. Scientific Beta Maximum Deconcentration Indices. (May).

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2016 Publications

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