PORTFOLIO
MANAGEMENT
RESEARCH
By With Intelligence

the journal of PORTFOLIO management

QUANTITATIVE STRATEGIES:
FACTOR INVESTING
8TH EDITION
volume 49 *number* 2

JANUARY
2023
jpm.*pm-research.com*

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the journal of PORTFOLIO management

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PERSPECTIVES Volume 49 | Issue 2

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Factor investing took off about 10 years ago, rooted in a vast body of empirical research accumulated over the prior decades. The asset pricing literature showed that factors such as size, value, and momentum explain the cross section of stock returns, while the mutual fund literature found little evidence for managerial skill beyond tilting toward factors. Taken together, these insights argue for harvesting factor premiums in a systematic, efficient manner. In an influential study commissioned by the Norwegian government pension fund, Ang, Goetzmann, and Shaefer (2009) even recommended including factor premiums in the strategic asset allocation, next to traditional asset class risk premiums. Although asset owners have generally been hesitant to go that far, factor investing has become an established investment approach. While quantitative investing has been around much longer, factor investing tends to make the choice of factors and their desired weights more explicit.

The fundamental difference between asset class risk premiums and factor premiums is that the former can be captured by following passive, capitalization-weighted indices with low turnover, while the latter are active investment strategies at heart. Index providers have attempted to commoditize factor strategies by introducing smart beta indices (also known as alternative beta indices), but these require various subjective choices, for example, regarding the factor definitions, weighting schemes, and rebalancing schedules. Factor indices do offer the benefit of simplicity and transparency and can serve as a benchmark for the evaluation of actively managed factor strategies.

Factor investing is sometimes referred to as risk factor investing, based on the notion that any premium must be a reward for some form of systematic risk. If factor premiums are indeed risk premiums, then they can be expected to persist in the future. Taking the value factor as an example, however, it is unclear why value stocks should command a risk premium over growth stocks but not the other way around, because both appear to be about equally risky using common risk metrics. An alternative explanation for the existence of factor premiums is that behavioral biases of investors cause systematic mispricing effects. These biases could stem from irrational behavior but might also be rationally induced by the institutional environment, such as incentive structures and regulatory frameworks. Given that such ambiguity applies to most factors, we prefer to stick to the shorter and more neutral term factor investing.

But how should the theory of factor investing be implemented in practice? The remainder of this article attempts to answer this question by discussing the selection of factors, how to combine them, and portfolio construction. Finally, we discuss next-generation developments in the factor investing space.

WHICH FACTORS?

The first step in factor investing is to identify the relevant factors, which is actually not as straightforward as one might think since an entire zoo of factors has emerged from the asset pricing literature (Cochrane 2011). In this section, we review the most popular and widely accepted factors, namely, size, value, momentum, quality, and low risk.

Size

The size factor captures the return difference between small-cap and large-cap stocks. Although universally accepted in asset pricing models, the size premium appears to have vanished in the United States following its discovery in the early 1980s, while never having been present in international markets to begin with. Asness et al. (2018) argue that a size premium does exist when controlling for the fact that most small stocks have poor quality characteristics. However, Blitz and Hanauer (2021b) show that this result does not carry over to international markets and that the US size alpha appears to be beyond the practical reach of investors, because the alpha that is observed ex post in time-series regressions cannot be captured by controlling for quality exposures ex ante. The size premium also lacks a strong economic rationale. It may have been difficult to invest in small stocks in the past, but such barriers have long since been removed with the introduction of small-cap mutual funds and, more recently, cheap ETFs on small-cap indices. The absence of a size premium does not render size irrelevant for factor investing, though. In particular, it can serve as a catalyst, because the premiums on other factors tend to be magnified in the small-cap space.

Value

Value, another classic factor, has also experienced performance issues. Over the last 40 years, the high-minus-low (HML) value factor of Fama and French (1993) has been flat in the US large-cap space. The particularly bad performance of value stocks during the FAANG-led growth rally of 2018–2020 triggered an open debate about the possible death of the value factor.[1] However, Blitz and Hanauer (2021a) show that a healthy long-term value premium still exists when applying a couple of sensible adjustments. For instance, the book-to-market ratio used in constructing HML is not particularly informative for firms with few tangible assets, such as Meta Platforms (formerly, Facebook). This issue can be addressed by incorporating intangibles and by considering earnings and cash-flow-related metrics, which are relevant for every firm. The value factor can also benefit from some basic risk management, like only comparing stocks within the same industry. Generic value strategies go structurally long in “cheap” industries (e.g., utilities) and short in “expensive” industries (e.g., tech). Such industry bets are better neutralized though, because they involve considerable volatility while adding little or nothing to return. The “resurrected” value factor represents a major improvement but, like any value strategy, remains vulnerable to massively widening valuation spreads.

Momentum

The momentum effect is hard to rationalize as a risk factor, which may explain why it has never been formally included in the Fama and French (1993, 2015) asset

[1] FAANG refers to Facebook (now named Meta), Apple, Amazon, Netflix, and Google (now, Alphabet).

pricing models. Nevertheless, it is widely accepted among academics and factor investors, if only because it is simply too strong to ignore. The main challenge with momentum is to avoid rare but devastating crashes. Techniques to deal with this include volatility scaling (Barroso and Santa Clara 2015) and applying the momentum strategy to idiosyncratic rather than total stock returns (Blitz, Hanauer, and Vidojevic 2020). Controlling turnover is also essential, because a naïve implementation of a momentum strategy can lead to excessive turnover. A notable issue with momentum is that while it is strong in the United States, Europe, and emerging markets, the premium is almost completely absent in Japan and China—the two biggest stock markets after the United States. The momentum factor can be strengthened by looking beyond past stock prices to gauge investor sentiment. Examples are earnings momentum (Novy-Marx 2015), earnings forecast revisions by analysts (van der Hart, Slagter, and van Dijk 2003), and sentiment derived from news articles.

Quality

Quality is a less clearly defined concept, open to many different interpretations. Kyosev et al. (2020) show that the main challenge with quality is to identify the metrics that work, such as gross profitability (Novy-Marx 2013) or measures of earnings quality (Sloan 1996; Hirshleifer et al. 2004), versus the ones that do not, such as traditional return on equity or profit margins. Asness, Frazzini, and Pedersen (2019) propose a composite quality-minus-junk factor consisting of about two dozen underlying variables. Another question with quality investing is whether it makes sense to buy a stock solely based on its quality characteristics, so with complete disregard for the price that one needs to pay for it. Novy-Marx (2013) refers to gross profitability as the other side of value, meaning that value and quality should always be considered in conjunction, as flip sides of the same coin.

Low Risk

The low-risk factor challenges the fundamental notion that higher (systematic) risk should be rewarded with a higher return. This goes against the heart of academic asset pricing models, which do not abandon the capital asset pricing model (CAPM) relationship between market beta and expected stock return but only extend it with additional priced factors. For practitioners, the low-risk factor is also not an easy one. Long-only investors need to recognize that having a similar return as the market with lower risk is also alpha, or find a way to overcome leverage constraints, for example, by leveraging through the asset allocation as already suggested by Black (1993). Long–short investors face a large, time-varying beta mismatch between the low-risk stocks in the long leg and the high-risk stocks in the short leg, which pushes risk management to its limits. At the same time, the presence of these strong limits to arbitrage may explain why the low-risk anomaly is such a persistent phenomenon. For an extensive review of the low-risk factor, we refer to Blitz, van Vliet, and Baltussen (2020).

The Rest of the Factor Zoo

Harvey and Liu (2019) argue that the rate of factor production in the academic literature is out of control, with over 400 factors published in top journals alone. In order to counter “factor fishing” or “p-hacking,” Harvey, Liu, and Zhu (2016) propose raising thresholds for *t*-statistics to 3, although that might not even be necessary because Hou, Xue, and Zhang (2020) find that many anomalies can already be rejected at conventional significance levels, solely by using a robust methodology that mitigates the impact of microcaps. So, how many “true” factors are there? We previously discussed how value, momentum, quality, and low risk have emerged as the core factors. However, these are not one-dimensional concepts but better interpreted as composite factors, derived from dozens of underlying subfactors. More factors probably exist beyond these core factors, but this requires separating the wheat from a considerable amount of chaff. In the final part of this article, we will provide some concrete examples for factor investing “beyond Fama-French.”

COMBINING FACTORS

Having discussed the individual factors, we next turn to the question of how to combine them. A natural starting point for a multifactor strategy could be to give each factor the same weight. DeMiguel, Garlappi, and Uppal (2009) find that although seemingly naïve, such 1/N approaches are generally hard to beat. The holy grail of factor investing is to come up with a successful factor timing strategy. Gupta and Kelly (2019) and Arnott et al. (2020) find that factor returns over the previous month have strong predictive power for the following month, but apart from this short-term phenomenon, there appears to be very little predictability in factor returns. In light of these results, Asness (2016) makes a compelling case to refrain from factor timing.

The strength of a 1/N approach is that it gives well-diversified, balanced exposure to the different factors. Balance, however, can be interpreted in several ways, in particular in periods when three factors go strongly against the fourth factor. Consider for example banking and insurance stocks during the Global Financial Crisis. Following large losses in 2008, these stocks exhibited very poor scores for momentum, quality, and low risk, but at the same time they had become very cheap on deep value measures, such as the book-to-market ratio. When giving the same weight to each factor, the value factor is effectively overwhelmed by the three other factors, and the portfolio may end up with a net negative value exposure. An alternative interpretation of factor diversification is that the portfolio should always have a net positive exposure to each factor. In the example here, this would mean giving a much bigger say to the value factor, in order to counterbalance the three other factors that are all pointing in the opposite direction.

In order to assess whether factors are properly balanced, one could also examine the performance of the multifactor portfolio over the economic cycle. Blitz (2022) finds that traditional business cycle indicators, such as NBER expansions versus recessions, high-versus-low inflation periods, or a positive-versus-negative ISM business outlook, have little relationship with factor returns. Factors do exhibit strong cyclical behavior but appear to follow their own distinct cycle. The main finding is that factors deliver a steady performance in most environments, except during periods of exuberance (e.g., the tech bubbles of 1998–2000 and 2018–2020) and junk rallies (e.g., tech in 2002–2003 and financials in 2009). There is no simple fix for this, as in times of exuberance, the problem is having too much value and too little momentum exposure, while during junk rallies, it is the other way around. Timing the various stages of the quant cycle is challenging, because the turning points are driven by abrupt changes in investor sentiment that do not appear to be related to fundamentals or macroeconomic news.

Instead of fixed weights, investors can also consider a dynamic, data-driven approach. For instance, Lewellen (2015) uses 10-year rolling Fama–MacBeth regressions based on 15 firm characteristics to predict next month stock returns. This approach has the advantage of being adaptive to changes in factor efficacy. If a factor stops working altogether, its weight is gradually reduced to zero. However, tilting toward the strongest factors over the lookback window, and away from the weakest ones, can also lead to underperformance if factors exhibit mean reversion in the long run. Data-driven approaches therefore require a careful tradeoff between adaptiveness on the one hand and procyclical performance chasing on the other.

Another question when combining factors is whether to use factor sleeves, that is, separate subportfolios for each factor, or an integrated approach. In theory, it is suboptimal to combine the results of multiple optimizations that are each based on partial information, compared to conducting one comprehensive optimization based on the full information set. For instance, the value sleeve could include a stock with great value characteristics but, at the same time, poor momentum, quality, and low-risk characteristics. The net contribution of such a stock to the overall portfolio factor characteristics would be negative. Blitz and Vidojevic (2018) show that this problem can be largely solved by blending the other factors into each sleeve with a small weight. In other words, if a value stock has very bad score on the other factors, it will be pushed down, and a stock with slightly less attractive value characteristics (but no red flags on the other factors) is selected instead. With this enhancement, combining single-factor sleeves or integrated optimization approaches tend to give very similar results.

PORTFOLIO CONSTRUCTION

Translating theoretical factors into a realistic investment portfolio is anything but straightforward. Academic factors are long–short portfolios, but in practice, factor investing is typically implemented with long-only portfolios. In support of this, Blitz, Baltussen, and van Vliet (2020) show that factors are at least as strong on the long side as on the short side. Academic factors also use a simple weighting formula and ignore trading costs, while in practice, costs matter and weights can be chosen more carefully. The widely used factor-construction methodology of Fama and French (1993) tends to inflate the magnitude of factor premiums by giving 50% weight to small- and micro-cap stocks that only comprise about 10% of total stock market capitalization. At the same time, breadth in the large-cap space is underutilized by applying capitalization weighting, which means that the 50–100 largest stocks dominate these results. A more efficient implementation gives less weight to both small-cap and mega-cap stocks.

Smart beta indices address some of these issues, for instance, by taking a liquid investment universe and limiting turnover. Smart beta indices are only rebalanced once per quarter or half year, however, and their performance can be highly sensitive to these arbitrarily chosen dates (Hoffstein, Sibears, and Faber 2019). Moreover, Blitz and Marchesini (2019) find that concentrating all the trades on just a few days every year tends to result in excessive market impact. The key to minimizing transaction costs and maximizing capacity is to follow the exact opposite trading style, that is, executing many small trades throughout the year to make the most efficient use of the liquidity offered by the market. Another issue with smart beta indices is that their trades are predictable due to their publicly available methodologies and that trades are even announced in advance of the effective date. This makes smart beta indices vulnerable to predatory trading by hedge funds and gaming by passive managers.

Academic factor portfolios and smart beta indices also apply little risk management. Stocks are ranked on their factor scores and then some simple weighting formula is used. Studies such as Ledoit, Wolf, and Zhao (2019) and Daniel et al. (2020) show that the risk-adjusted performance of factor portfolios can be improved substantially by using information from the covariance matrix of past stock returns. This resembles the approach taken by active factor investing managers, who typically use expected alphas, a risk model, and a transaction cost model as inputs for an optimization problem that maximizes risk-adjusted returns after costs.

BEYOND FAMA–FRENCH

The value, quality, and low-risk factors are quite slow, with average holding periods of multiple years. Momentum is faster due to its lookback period of about one year, but the literature has uncovered many signals that are much faster still. For instance, short-term reversal and short-term industry momentum both have a lookback period of just one month. Such fast signals are often dismissed because of concerns that they do not survive after accounting for transaction costs. However, Blitz et al. (2022) show that this challenge can be overcome by combining multiple short-term signals, restricting the universe to liquid stocks, and using cost-mitigating trading rules. With an efficient implementation, short-term signals can offer a strong net alpha that enables investors to expand the efficient frontier.

Classic factors are primarily derived from stock prices and the information in financial statements. Other commonly used data include analyst forecasts and prices observed in other markets, such as the bond, option, and shorting markets. In recent years, however, the number of available datasets has exploded, thus offering exciting opportunities for next-gen factor investing. Sources for alternative data include financial transactions, sensors, mobile devices, satellites, public records, and the internet, to name a few. Text data—such as news articles, analyst reports, earnings call transcripts, customer product reviews, or employee firm reviews—can be converted into quantitative signals using natural language processing techniques that are becoming increasingly sophisticated. All this data can be used not only to create new factors but also to enhance existing factors. For instance, traditional value factors have been criticized for only including tangible assets that are recognized on the balance sheet, while many firms nowadays have mostly intangible assets, such as knowledge capital, brand value, or network value. For estimating the value of knowledge capital, for example, one could consider patent data.

Next to the big data revolution there has also been an explosion in computational power. This allows investors to move beyond basic portfolio sorts or linear regressions, and apply more computationally demanding machine learning techniques, such as random forests and neural networks. The main advantage of machine learning is that it can uncover nonlinear and interaction effects. Studies such as that by Gu, Kelly, and Xiu (2020) report substantial performance improvements when applying machine learning (ML) to a large set of traditional input variables. However, there are also challenges. For instance, the turnover of ML models can be excessive as the models are typically trained on predicting next one-month returns, in order to have a sufficient number of independent observations (Leung et al. 2021). Also, the interpretability of ML model outcomes is not straightforward. Thus, machine learning has the potential to further push the frontiers of factor investing, but various challenges need to be overcome.

Finally, the growing interest in sustainability integration presents another big opportunity for factor investing. Sustainability can be quantified with broad ESG (environmental, social, and governance) scores or more specific metrics, such as carbon footprints, that are widely available nowadays. Because such sustainability scores are conceptually similar to factor scores, it is rather straightforward to incorporate them in the portfolio optimization problem, for instance, in the form of hard constraints or by trading them off against each other in the objective function as in Chen and Mussalli (2020). In general, a sizable amount of sustainability can be incorporated into factor portfolios without materially affecting factor exposures. In this way, factor investing can marry the twin objectives of wealth and wellbeing.

FINAL WORDS

Factor investing strategies were severely challenged by the quant crisis of 2018–2020, during which large growth stocks dominated the market (Blitz 2021). Investors wondered whether factor premiums had been arbitraged (or commoditized) away, or whether factors had simply fallen victim to their own success. Since then, however, factor strategies have made a strong recovery, with the burst of the growth bubble and markets going in risk-off mode. Although the quant crisis forced factor investors to acknowledge that there is room for improvement, the basic premise behind factor investing remains intact. This is not to promote complacency with the status quo, but making the case for a thoughtful evolution of factor investing. Today's environment is more exciting than ever, with quant investors being able to automate higher value-add tasks that would traditionally be provided by fundamental analysts. While it is great to see plenty of opportunities for quants to broaden their alpha opportunity set, the ability to rationalize and synthesize observed return patterns will be key in meaningfully advancing investment processes to the benefit of clients with diverse investment objectives.

ACKNOWLEDGMENTS

The author thanks Harald Lohre and Matthias Hanauer for valuable comments on an earlier version of this article.

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