Academic, Practitioner, and Investor Perspectives on Factor Investing

JOSEPH CERNIGLIA AND FRANK J. FABOZZI

JOSEPH CERNIGLIA
is an adjunct professor in the Courant School of Mathematics at New York University in New York, NY, and a visiting scholar at the University of Pennsylvania in Philadelphia, PA.
jac355@nyu.edu

FRANK J. FABOZZI
is a professor of finance at the EDHEC Business School in Nice, France.
frank.fabozzi@edhec.edu

In this article, we explore the current state of affairs, critical issues, and practical considerations associated with factor research and factor investing. We examine these aspects from the perspectives of academics, practitioners, and investors. Although much of the research overlaps among these three perspectives, there are differences relevant to all parties, particularly individual investors. Our article furthers the understanding of factor investing for investors by integrating the thinking across these different perspectives.

What are factors? Factors are securities that have been grouped into buckets with similar characteristics. Factors have been labeled style premiums, smart beta, and anomalies. They are widely used to understand the risk and return properties of similar securities in investment thinking and investing. The research on factors is extensive, with over 40 years of effort by academics and practitioners.

There are many types of factors for different assets. Some are constructed from cross-sectional characteristics such as size, value, momentum, and quality. Others can be derived from top-down economic measures such as interest rates, inflation, and economic growth. Factors span geographies and asset classes (e.g., equities, bonds, commodities, and currencies). In currencies, some examples include momentum, volatility, and carry. In fixed income, there are factors related to credit, quality, and other characteristics. In equities, the number of factors is large, with published research on over 400 characteristics.

More recently, factor investing has been a popular investment approach. Broadly, factor investing represents an investment strategy to select securities based on a set of static rules. Factor investment products combine the characteristics of active and passive products. They can be considered passive because a factor portfolio is constructed from static rules applied in an algorithmic process. These products also share characteristics of actively managed portfolios, most notably by their tracking error (sometimes large tracking error) relative to the market portfolio.

THE ACADEMIC PERSPECTIVE

Academic research on factors dates back to the 1930s, when Graham and Dodd [1934] wrote about the value premium. Two equilibrium models were formulated for the relationship between asset returns and factors: the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT). The CAPM, introduced in 1964, provided an important fundamental principle of modern finance, stating that a stock's return is a function of its market sensitivity. In 1976, Ross developed APT, demonstrating that the returns of securities can be modeled as a function of various factors. His theory provides an empirically based framework, beginning the tradition of using multiple factors as research tools and providing a way to understand the risk and return characteristics of different securities.

In the late 1970s, academics began to identify groups of securities that outperformed the market portfolio. That is, abnormal profits are possible if investors can identify the right cross-sectional characteristics. These groupings were referred to as *anomalies*. Early work on identifying factors includes that by Basu [1977], who showed that inexpensively priced stocks outperform on a risk-adjusted basis. Banz [1981] found that small-capitalization stocks outperform large-capitalization stocks. The search for new anomalies persists, and their role continues to be debated in modern financial research.

In academia, the current state of factor research focuses on several research questions inspired by John Cochrane's [2011] American Finance Association 2011 presidential address. He labeled the current state of research a "factor zoo," highlighting that many papers over the last three decades have identified different factors as providing returns above risk-adjusted models such as the CAPM or the Fama–French three-factor model. Solid theories support many of these factors in why they should deliver performance, and a large body of empirical work has reported that these returns are statically significant. However, the large number of these factors raises concerns.

Specifically, John Cochrane in his presidential address identified the following three critical questions:

1. Which factors are independent?
2. Which factors are important?
3. Why do factors move prices?

Academic researchers have begun to examine these questions. Over the last few years, multiple papers have addressed these critical issues. One approach is to set a higher statistical bar to determine whether factors predict returns reliably. Harvey, Liu, and Zhu [2014] reviewed 300 variables published in various journals over 30 years. To address concerns, they proposed a framework for the multiple testing problems associated with examining the expected return and recommended much higher levels of statistical significance as a benchmark. They also emphasized that a factor that is derived from theory should have a lower statistical benchmark than one derived from pure empirical work.

Green, Hand, and Zhang [2016] attempted to find independent and significant cross-sectional factors in equities from a universe of 94 factors from 1980–2014. Their research indicated 12 factors are significant after adjusting for the influence of micro-cap stocks and concerns regarding data-snooping. They concluded that the number of independent determinants of asset returns is small, and the magnitude of these returns has been diminishing since 2003.

Another concern is whether returns to factors disappear as more investors learn about them. McLean and Pontiff [2016] examined the performance of 97 factors out of sample both before and after the factor was published. They showed that returns to factors are over 50% lower after publication. Examining the performance of 38 factors in these two out-of-sample periods—the prepublication period and the post-publication period—Linnainmaa and Roberts [2016] reported that at most 12 of these factors earn significantly positive returns in both out-of-sample periods. They concluded that datasnooping bias could be distorting the research on other factors in their study.

Machine learning techniques are being used by financial researchers to make sense of the high dimensionality of factors. Feng, Giglio, and Xiu [2017] tested the marginal importance of a factor for pricing assets using the statistical technique of least absolute shrinkage and selection operator. Their methodology selects the best parsimonious model out of the large set of existing factors. Similar to the research of others, they identified a small set of factors that seem to be significant and stable in explaining returns.

Combining factors or signals is a vital area of research that has received increased attention. How factors are combined is as important as what factors are used in a model. Finding the optimal approach to combining factors is as much an art as it is a science. Techniques range from bootstrapping human judgment to linear regressions to machine learning approaches. Well-known models in academia include Piotroski's [2000] F-score and Mohanram's [2005] G score, which combine traditional fundamental factors into a composite score to rank stocks. Asness, Frazzini, and Pedersen [2017] created a quality score using 21 different factors.

Novy-Marx [2016] raised several important issues related to these factor strategies. He argued that the performance of these strategies often suffers from bias caused by overfitting and selections biases and therefore backtesting needs to be carefully designed. While acknowledging that combining signals can lead to better performance, he recommends that the marginal contribution of each factor be evaluated individually. Variable selection for models and combining variables is an area in which there are many open research questions.

Transaction costs are another important topic that affects our understanding of factors. Many studies on anomalies ignore the costs associated with trading, thereby overstating the returns these strategies achieve. Recently, some studies have provided a better understanding of transaction costs. Novy-Marx and Velikov [2015] evaluated the transaction costs associated with a large number of well-known factors within a mean–variance-efficient portfolio framework. In addition, they proposed three strategies (limiting trading to low-transaction-cost stocks, lowering the frequencies of rebalancing, and applying more stringent spread criteria for trading) to lower the trading costs for implementing strategies.

Over the past 30 years, we have seen in the market events that have moved asset prices spectacularly—the Dot-Com Crash (2000–2001), Asian Financial Crisis (1997), Great Financial Crisis (1996–2007), the Great Moderation (1990s–2000), and the European Debt Crisis (2010). In these periods, we observe a complex link between factor returns and macroeconomic outcomes. Claessens and Kose [2018] surveyed the literature on asset prices and macroeconomic environments, providing insights on some of the theoretical mechanisms driving these relationships. We think more work needs to be done to better understand the link between factor returns and the macroeconomic environment.

THE PRACTITIONER PERSPECTIVE

Practitioners aligned their investment strategies with groups of stocks, such as value stocks (Graham and Dodd [1934]), growth stocks (Fisher [1958]), or other stock characteristics such as income. Historically, these factors were viewed as investment styles that are grounded in an underlying investment philosophy and economic rationale.

For active managers, factors have been part of the investment tool kit for four decades. As a research tool, factors became vital to designing investment strategies, managing risk, and constructing portfolios. Currently, although factors affect practitioners in many ways, we focus on the following four in our discussion: (1) increased impact of flows into factor portfolios, (2) timing of factors, (3) distinguishing value added of active managers from factor investment strategies, and (4) the benefits of innovation.

As factors move from a research tool in academia to investment products gathering assets, the problem of crowding magnifies. Crowding occurs when investors hold positions with similar investment theses. A contagion effect can be induced when investors hold overlapping positions and react simultaneously to information related to the investment thesis. The rules-based approach of factor strategies is likely to contribute further to the negative impact of crowding.

Decaying returns to factor strategies can result from crowding. Flows into exchange-traded fund factor strategies and active managers compete away the excess return opportunity in securities. Crowding can contribute to overvaluation, pushing valuations beyond reasonable levels and reducing potential future returns.

Crowding affects the liquidity of the individual securities held in factor strategies. Large withdrawals after substantial inflows create an environment prone to the rapid unwinding of positions. These trades are not driven by the changing underlying fundamentals of securities. Khandani and Lo [2011] documented this effect in August 2007 when several highly successful quantitative long–short hedge funds realized large losses. A number of quant managers liquidated similar positions, causing significant selling pressure that induced larger price movements. Factors portfolio trading could contribute to indiscriminate buying of stocks that adds to the potential for crowding. Liquidity events are relatively infrequent events, making crowding a difficult concept to model.

Factor timing is an active topic of research in the industry. Practitioners debate whether it is possible to increase the allocation to factors when their expected return is high and reduce the allocation when the expected returns are low. The potential returns to a successful strategy could be very large and beneficial to clients. It also provides an opportunity for active investors to distinguish their returns from returns of a factor investing strategy.

Factor timing is a challenging endeavor. Asness [2016, p. 2] argued that "good factors and diversification … trump the potential of factor timing." He made several strong points regarding the risk of timing strategies. However, as factors move increasingly from a research tool to an investment tool with an increasing amount of assets, the opportunity set to allocate to various factors could increase.

Innovation in investing thinking provides an opportunity to challenge conventional thinking. There is a strong economic rationale regarding why varying the allocation to factors is a viable strategy. If we know that the underlying fundamentals of stocks are influenced by the economic environment, then the aggregate cross-sectional characteristics are likely to be sensitive to macroeconomic risks or other types of market risks. As researchers and investors, we believe that advancements in econometric techniques and machine learning algorithms provide analytical tools to aid in discovering ways to manage the factor exposure of portfolios more actively. Cerniglia and Kolm [2017], for example, showed how machine learning can contribute to forecasting factor returns in different economic environments.[1]

In the active management industry, a mounting challenge is how to distinguish manager performance from factor performance. This is an issue many managers will have to address with clients, consultants, and plan sponsors. Bender, Hammond, and Mok [2014] showed that up to 80% of active excess return garnered by managers can be explained by the factor exposures of their portfolios. Bosse, Wimmer, and Philips [2013] provided empirical evidence that factor tilts have been a primary driver of active bond fund performance.

Factors might be highly correlated with active managers but are not identical. Although 80% is a large number, the 20% difference could be a significant determinant of performance difference that is worth the additional costs. Active managers have the opportunity to innovate relative to the more rule-based factor strategies. As the investing environment changes, active managers have the flexibility to adjust quickly relative to a rules-based approach.

Innovation is critical for success in active management. Developing new factors is one useful method for improving the performance of active managers. Cerniglia, Fabozzi, and Kolm [2016] provided an overview of how better research design can be applied to developing alpha-generating factor strategies. Tetlock and Gardner [2015] showed how research from the field of decision science can assist in developing more accurate predictions.

New factors will continue to be developed. Some of these factors will be created from Big Data sources as investment professions continue to embrace new data sources as a competitive advantage (see Fortado, Wigglesworth, and Scannell [2017]). How useful new data will be is an open debate. Most of the data we use in factor research were created for investment research. In contrast, much of the Big Data available were not created for investment research; those data were gathered from electronic devices, businesses, and governments as part of their normal course of business. These data are often incomplete and fragmented, and their relationship to financial markets could be spurious. As these new data are repurposed to develop new factors, new challenges will arise that require experience, domain knowledge, and technical expertise.

THE INVESTOR PERSPECTIVE

Recently, factors have become an increasing fashionable way to invest assets. Factor strategies available through ETFs are becoming increasingly popular, as evidenced by the number of factor ETFs available to trade, the number of firms marketing ETFs, and the amount of assets under management in these factor ETFs. *The Economist* [2018] estimated that $658 billion is in factor ETFs.

Factor strategies bring innovative investment options to investors. They give investors the ability to access the returns and risks characteristics of a particular investment style in a cost-effective and efficient standardized investment product. Investors can acquire exposure to a range of styles with intraday trading on exchanges. Previously, investors had to pay much higher fees to get access, if it was possible to obtain access at all. Factors present investors with the opportunity to gain exposure to factors across asset classes that previously were unavailable. They provide an essential tool to understand the risk and return characteristics of a portfolio.

Investors should appreciate all the risk associated with factor strategies. Risks extend beyond the risk associated with the named characteristics used in the rules applied to securities in creating the factor portfolio. For example, the MSCI Value Index is constructed from three factors (book value to price, 12-month forward earnings to price, and dividend yield), with limited portfolio turnover. In general, value strategies have time-varying risk exposures to other factors, such as interest rates, economic growth, price momentum, and beta, among other characteristics.

Without carefully controlling for these other risks, many investors might be exposing themselves to unrecognized risks. Most importantly, these uncontrolled risks vary through time and a fixed portfolio re-balancing horizon could escalate these risks.

There are other important questions that investors should be asking about these products:

- Do factors have expectations of higher returns than the market portfolio?
- Can we expect the returns to factors to persist?
- How do we measure and monitor the risks associated with factor strategies?

Daniel and Moskowitz [2016] examined these questions for the momentum factor. From 1929 to 2015, they found that momentum has exhibited very strong performance in terms of average returns and Sharpe ratios. However, they noted that "there are relatively long periods over which momentum experiences severe losses or crashes." Along with these points, Daniel and Moskowitz highlighted several other interesting characteristics such as the asymmetry in returns between long and short sides of a momentum portfolio and the frequent option-like characteristics of the return series. Investors should be aware that other factors such as value, income, and quality also have their own unique risk and return properties.

In employing a factor strategy in a portfolio, an investor should determine whether the objective in selecting the strategy is for (1) diversification or (2) enhancing returns. Factors sometimes offer unique diversification benefits because many strategies have low correlations relative to traditional asset classes. Factor portfolios can be used to hedge away specific factor risk if desired. These factor strategies could enhance returns because some strategies have delivered larger returns relative to market portfolios. Factor strategies with good liquidity could provide an opportunity to execute tactical trades within a more strategic allocation strategy.

SUMMARY

Moving from a research tool to an investable product has both positive and negative implications. Factor-based strategies bring a new dynamic to the market that investors need to recognize. On the positive side, factor portfolios proved an inexpensive way of acquiring exposure to various rule-based strategies. Factors continue to be powerful research tools for both academics and practitioners. The negative effect is that much of what we know about factors from previous research might not be as relevant going forward. As the amount of assets under management that employs factor-based strategies grows, return potential of these strategies can decline while the risk of these strategies increases. Thoughtful and innovative research will be the key to the success of these strategies for researchers and investors.

ENDNOTE

[1]Lopez de Prado [2018] thoroughly reviews the difficulties of implementing machine learning in asset management, bridging the gap between academia and practice.

REFERENCES

Asness, C.S. "The Siren Song of Factor Timing." *The Journal of Portfolio Management*, Vol. 42, No. 5 (2016), pp. 1-6.

Asness, C.S., A. Frazzini, and L.H. Pedersen. "Quality Minus Junk." SSRN, June 5, 2017. https://ssrn.com/abstract=2312432.

Banz, R.W. "The Relationship between Return and Market Value of Common Stocks." *Journal of Financial Economics*, Vol. 9, No. 1 (1981), pp. 3-18.

Basu, S. "Investment Performance of Common Stocks in Relation to Their Price–Earnings Ratios: A Test of the Efficient Market Hypothesis." *The Journal of Finance*, Vol. 32, No. 3 (1977), pp. 663-682.

Bender, J., P.B. Hammond, and W. Mok. "Can Alpha Be Captured by Risk Premia?" *The Journal of Portfolio Management*, Vol. 40, No. 2 (2014), pp. 18-29.

Bosse, P., B.R. Wimmer, and C.B. Philips. "Active Bond-Fund Excess Returns: Is It Alpha... or Beta." Vanguard Research, September 2013. https://personal.vanguard.com/pdf/s809.pdf.

Cerniglia, J.A., F.J. Fabozzi, and P.N. Kolm. "Best Practices in Research for Quantitative Equity Strategies." *The Journal of Portfolio Management*, Vol. 42, No. 5 (2016), pp. 135-143.

Cerniglia, J.A., and P.N. Kolm. "Statistical vs. Machine Learning Approaches in Buy-Side Research." Presentation at Data Science in Quant Finance Conference at NYU Courant, 2017.

Claessens, S., and M.A. Kose. "Frontiers of Macrofinancial Linkages." Paper no. 95, Bank for International Settlement, January 2018. https://www.bis.org/publ/bppdf/bispap95.htm.

Cochrane, J.H. "Presidential Address: Discount Rates." *The Journal of Finance*, Vol. 66, No. 4 (2011), pp. 1047-1108.

Daniel, K., and T.J. Moskowitz. "Momentum Crashes." *Journal of Financial Economics*, Vol. 122, No. 2 (2016), pp. 221-247.

The Economist. "Maxing the Factors." February 1, 2018.

Feng, G., S. Giglio, and D. Xiu. "Taming the Factor Zoo." Chicago Booth research paper no. 17-04, SSRN, August 31, 2017. https://ssrn.com/abstract=2934020.

Fisher, P.A. *Common Stocks and Uncommon Profits and Other Writings*. Hoboken, NJ: John Wiley & Sons, 1958.

Fortado, L., R. Wigglesworth, and K. Scannell. "Hedge Funds See a Gold Rush in Data Mining." *Financial Times*, August 28, 2017.

Graham, B., and D. Dodd. *Security Analysis*. New York: McGraw-Hill, 1934.

Green, J., J.R.M. Hand, and X.F. Zhang. "The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns." October 14, 2016. https://ssrn.com/abstract=2262374.

Harvey, C.R., Y. Liu, and H. Zhu. "... and the Cross-Section of Expected Returns." *The Review of Financial Studies*, Vol. 29, No. 1 (2014), pp. 5-68.

Khandani, A.E., and A.W. Lo. "What Happened to the Quants in August 2007? Evidence from Factors and Transactions Data." *Journal of Financial Markets*, Vol. 14, No. 1 (2011), pp. 1-46.

Linnainmaa, J.T., and M.R. Roberts. "The History of the Cross Section of Stock Returns." Working paper no. 22894, National Bureau of Economic Research, December 2016.

Lopez de Prado, M. *Advances in Financial Machine Learning*. Hoboken, NJ: John Wiley & Sons, 2018.

McLean, R.D., and J. Pontiff. "Does Academic Research Destroy Stock Return Predictability?" *The Journal of Finance*, No. 71, No. 1 (2016), pp. 5-32.

Mohanram, P.S. "Separating Winners from Losers among Low-Book-to-Market Stocks Using Financial Statement Analysis." *Review of Accounting Studies*, Vol. 10, No. 2–3 (2005), pp. 133-170.

Novy-Marx, R. "Testing Strategies Based on Multiple Signals." Working paper, Simon Graduate School of Business, 2016. http://rnm.simon.rochester.edu/research/MSES.pdf.

Novy-Marx, R., and M. Velikov. "A Taxonomy of Anomalies and Their Trading Costs." *The Review of Financial Studies*, Vol. 29, No. 1 (2015), pp. 104-147

Piotroski, J.D. "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers." *Journal of Accounting Research*, Vol. 38, Supplement (2000), pp. 1-41.

Tetlock, P.E., and D. Gardner. *Superforecasting: The Art and Science of Prediction*. New York: Crown Publishers, 2015.