How Misunderstanding Factor Models Set Unreasonable Expectations for Smart Beta

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KEY FINDINGS

- Smart beta originates from standard factor models and hence is bound by their limitations.
- Time-varying factor performance is inherent in factor models, suggesting that potential poor returns of smart beta strategies for extended periods should not be surprising.
- Smart beta factors' performance tends to decay after publication, suggesting that a transparent, passive approach to factor investing is suboptimal.
- Efforts to make smart beta smarter will not be sufficient to succeed in the complex stock market. It takes a fully active, dynamic, multifactor approach (aka "smart alpha") based on proprietary research to outperform the market.

ABSTRACT

The poor performance of some smart beta strategies in recent years should not be surprising. After all, the standard factor pricing models from which the strategies draw their well-known factors inevitably include factors that may fall out of favor, sometimes for extended periods, as market conditions change. Some smart beta providers are exploring factor timing and multifactor portfolios in an effort to provide more consistent return premiums and assuage investor disappointment. Despite this move away from largely passive management and toward more active management, smart beta strategies remain subject to limitations imposed by the standard factor models underpinning them, including a relatively narrow focus on a handful of generic factors and a failure to take into account correlations between factors. Overcoming these limitations requires further steps toward a fully active, dynamic, multifactor approach (aka "smart alpha").

Smart beta has been one of the fastest growing investment products over the last decade. Global assets invested in smart beta exchange-traded funds (ETFs) and exchange-traded products (ETPs) reached $1.67 trillion with a five-year annual growth rate of 22.5% by the end of June 2024.[1] Despite its rising popularity, smart beta investing has often failed to live up to its hype. Many smart beta strategies, notably those based on the value factor, underperformed the market over the past 15 years.[2]

For those with a clear understanding of factor models—the root of smart beta and factor investing in general—the prolonged underperformance of some smart beta

[1] See ETFGI (2024).

[2] See, for example, Riding (2019a, 2019b), Johnson (2020a, 2020b), and McCann (2020). For the performance over earlier periods, see Malkiel (2014) and Glushkov (2016).

strategies should not be surprising. The models underpinning smart beta strategies acknowledge time-varying factor performance, suggesting that periods of poor returns are inevitable. We explore several structural limitations of smart beta that help explain its recent underperformance. This extends the argument in Jacobs and Levy (2014b), which compared the characteristics of smart beta with those of active, dynamic, multifactor strategies ("smart alpha") by tracing these limitations to the factor models underlying the smart beta strategies.[3]

FROM FACTOR MODELS TO SMART BETA

Smart beta strategies aim to outperform the capitalization-weighted stock market by using alternative weighting methods that emphasize one or a few factors that research suggests have historically outperformed the market.[4] Factor models are arguably the genesis of smart beta. These factors are typically selected from standard multifactor models such as the Fama–French three- or five-factor models.

To fully understand smart beta, it is essential to understand the two key implications of factor models: The chosen factors 1) can explain much of the cross section of average stock returns and 2) capture time-series variation in stock returns.[5] Taking the Fama–French three-factor model as an example, the first implication indicates that a cross section of average returns is negatively related to market capitalization (size) and positively related to book-to-market ratio (value). The second implication suggests that the excess returns of small stocks over large stocks and of value stocks over growth stocks are time varying. That is, factor models explicitly allow the possibility that selected factors (such as small size or value) may fall out of favor and, as a result, portfolios emphasizing these factors may underperform for extended periods of time.

Smart beta providers who claim that their strategies can beat the broader market with some consistency are implicitly focusing on the first implication and overlooking the potential prolonged underperformance inherent in the second implication. If investors mistakenly expect smart beta to deliver consistent returns over time, it could be because smart beta providers have not properly educated them about the strategy's inherent variability and risks. We offer evidence of several fundamental shortcomings of smart beta based on factor models and discuss how they explain its more recent underperformance.

AVERAGE RETURNS VERSUS CONSISTENT RETURNS

The efficacy of any smart beta strategy ultimately depends on the performance of its underlying factor(s). Smart beta strategies seek exposure to certain factors that have historically delivered a positive risk-adjusted return. These factor premiums

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[3] For other skeptical views on smart beta, see, for example, Malkiel (2014), Jacobs (2015), and Jacobs and Levy (2015).

[4] Such factors include size (Fama and French 1993, 2015), value (Fama and French 1993, 2015), momentum (Carhart 1997), low volatility (Frazzini and Pedersen 2014), and quality (Asness, Frazzini, and Pedersen 2019), among others.

[5] Both implications are derived from time-series regression, the traditional approach for testing factor models. For example, Fama and French (1993) construct 25 test portfolios formed on size and book-to-market equity. They then test whether their three-factor models, which include the market factor, can explain a wide range of average returns of these test portfolios. They do so by running a time-series regression of each test portfolio's excess return on the returns of their factor-mimicking portfolios. A zero intercept across all test portfolios leads to the first implication; and the slopes (factor loading estimates) and R^2 provide evidence for the second implication.

are measured as the average returns over time to factor portfolios constructed using standard, time-series factor models. For example, the four non-market factor portfolios of the Fama–French five-factor model measure excess returns to portfolios sorted by size (SMB, or small minus big), value (HML, or high minus low book-to-market ratio), profitability (RMW, or robust minus weak), and investment (CMA, or conservative minus aggressive).

Each of these factor portfolios had a significantly positive average return (at least at the 10% level) in the United States over the period from July 1963 to March 2024 (729 months). However, SMB delivered negative returns in 352 of those months (48% of the time), while HML, RMW, and CMA experienced negative returns in 334 months (46%), 316 months (43%), and 342 months (47%), respectively.[6] Furthermore, SMB, HML, and CMA posted more negative monthly returns in the second half of the period, from November 1993 to March 2024, than in the first half. Each of these three factors delivered a negative return about 50% of the time in the second half of the period.

The unstable time series of factor premiums does not directly explain the recent underperformance of some smart beta strategies, but it does suggest that underperformance—even extended underperformance—should not come as a surprise.[7] Smart beta is designed to capture exposures to factors with historically positive average premiums; it is less focused on the consistency of those returns over time.

RELYING ON HISTORICAL RETURNS

Time-series modeling á la Fama–French considers average portfolio performances of a few factors over a long stretch of time. Inherent in smart beta strategies that rely on these results is the expectation that the future will likely resemble the past. This is not always borne out.[8] Some hypothetical factor premiums based on historical averages, notably the value factor, haven’t held up in practice.[9]

Exhibit 1 plots on a natural log scale the cumulative gross returns of the popular and generic Fama–French four non-market factor portfolios in the United States for the period July 1963 to March 2024. SMB, HML, and CMA recently experienced declines of 25% or more from their peaks.[10] Although RMW has performed well since 2021,

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[6] Return series for these factors are available in Ken French’s data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Akey, Robertson, and Simutin (2024) find that factor returns in French’s data library can vary substantially by vintage (i.e., when the data were downloaded) and recommend that researchers disclose the factor vintage they are using for replicability. We use the March 2024 vintage (the most recent as of this writing).

[7] Aghassi et al. (2023) provide both risk-based and behavioral explanations for the inevitable short-term—occasionally, prolonged—performance drawdowns of factor investing. Risk-based theories assert that long-term factor premiums should be compensation for bearing the risk of suffering the potential short-term underperformance. Based on behavioral explanations, investors earn factor premiums by exploiting mispricing caused by investors’ irrational preferences or beliefs. However, if such mispricing persists longer than expected before the pricing corrects, periods of extended underperformance can occur.

[8] Jacobs and Levy (2014b) suggested that overcrowding due to the growing investment in smart beta factors could result in decaying factor premiums and occasional factor crashes.

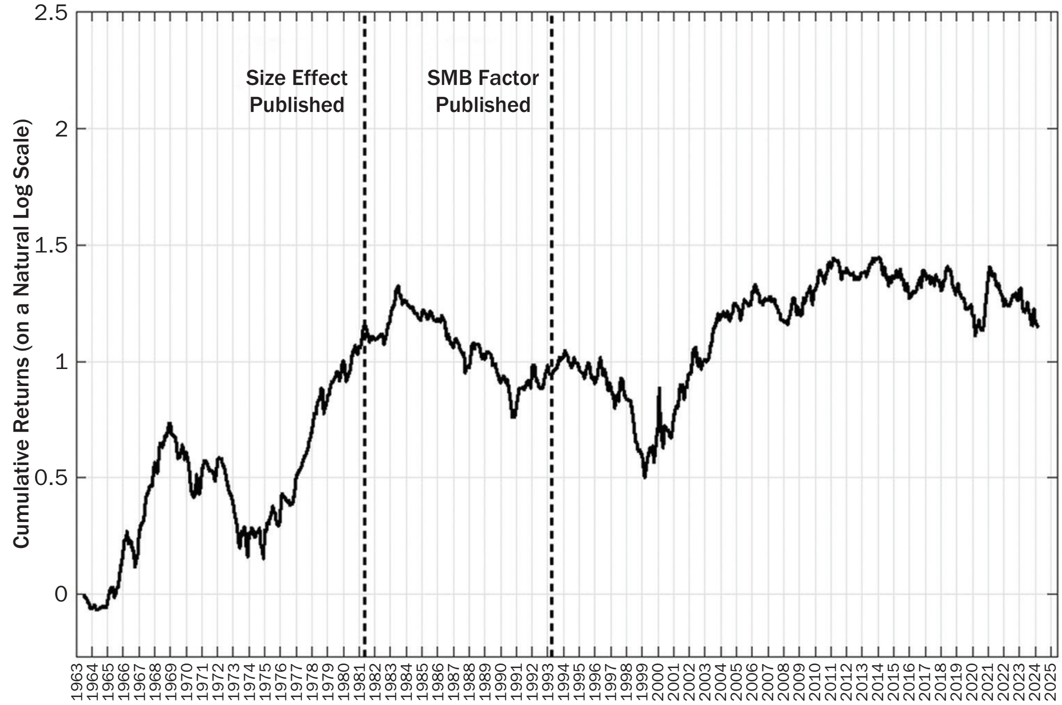
[9] For example, Fama and French (2021) reported that the value premium was, on average, much lower in the second half of the July 1963–June 2019 period than in the first half. However, they pointed out that the high volatility of value premiums makes it challenging to draw definite conclusions about whether the value premium has indeed declined in the second half.

[10] The most recent peak-to-trough drawdown in cumulative factor returns was for SMB, –28% over the 73-month period from March 2014 to March 2020, and for HML, –58% over the 165-month period from January 2007 to September 2020. CMA suffered a peak-to-trough drawdown of –25% over the 90-month period from May 2013 to October 2020, before it had two more recent drawdowns of –11% over the 2-month period from June to July 2022 and –18% over the 14-month period from January 2023 to February 2024.

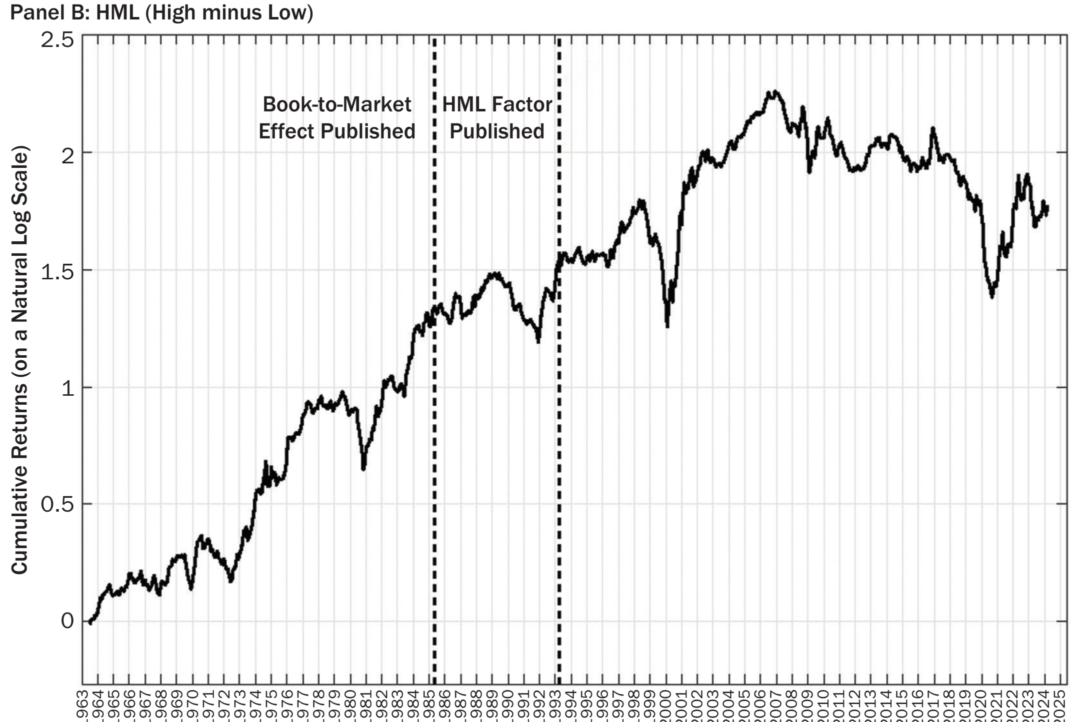
EXHIBIT 1

Cumulative Returns of Fama–French Factors, July 1963–March 2024

Panel A: SMB (Small minus Big)



Panel B: HML (High minus Low)

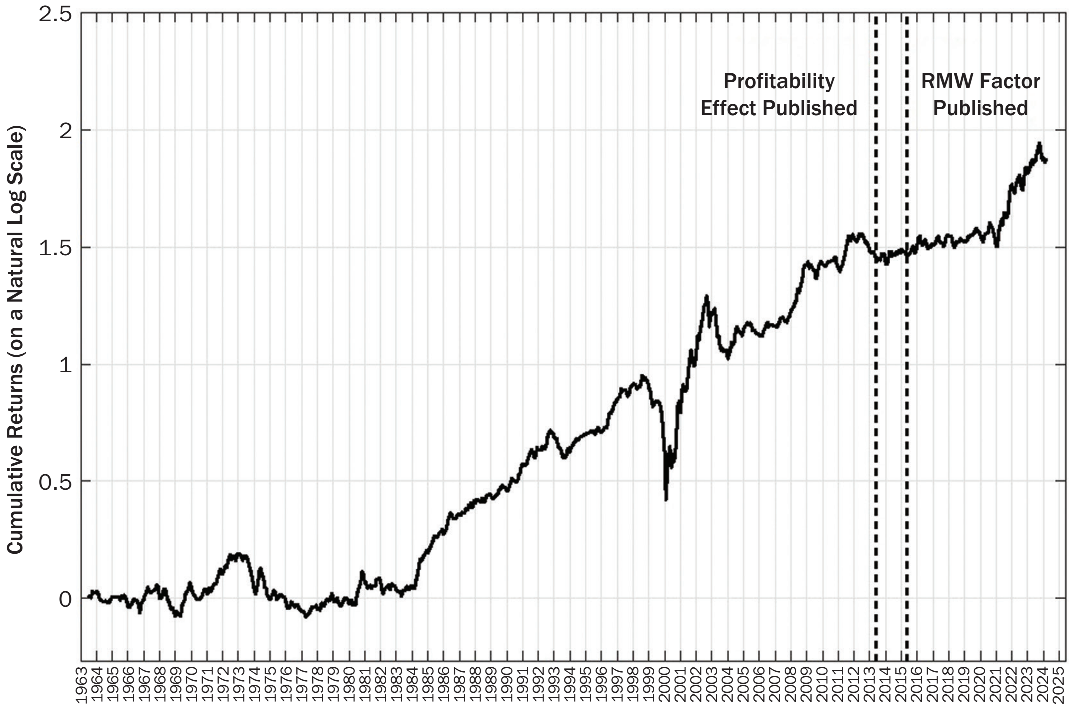


(continued)

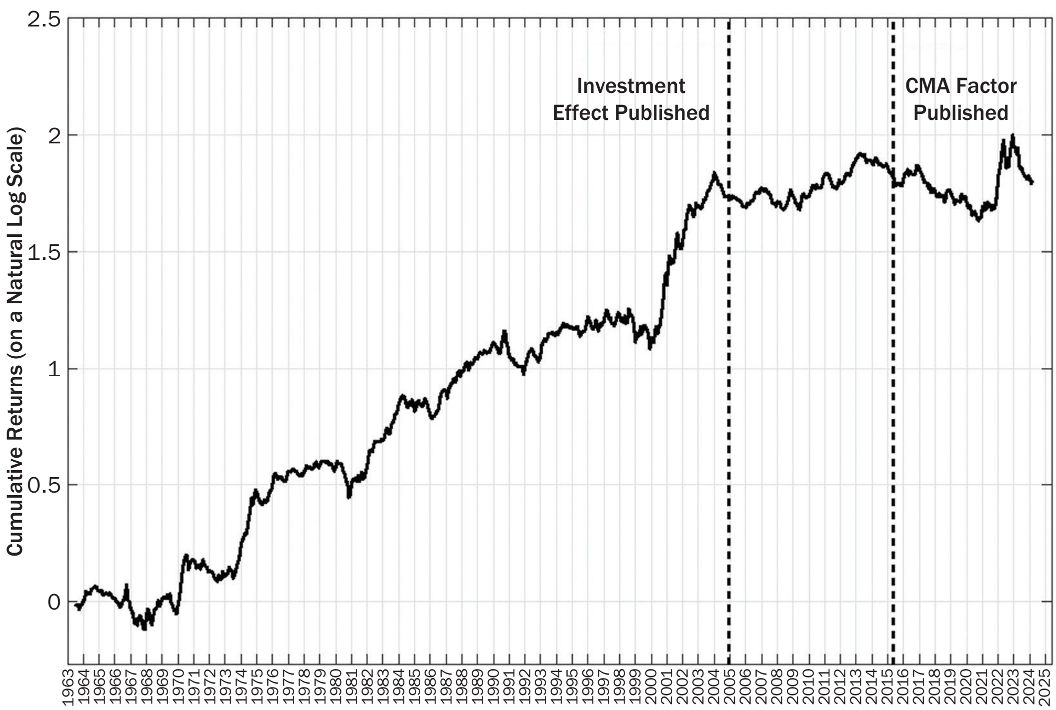
EXHIBIT 1 *(continued)*

Cumulative Returns of Fama–French Factors, July 1963–March 2024

Panel C: RMW (Robust minus Weak)



Panel D: CMA (Conservative minus Aggressive)



NOTES: Following McLean and Pontiff (2016), we identify Banz (1981), Novy-Marx (2013), and Titman, Wei, and Xie (2004) as the publications first documenting the return predictability of size (SMB), gross profitability (RMW), and investment (CMA), respectively. We identify Rosenberg, Reid, and Lanstein (1985) as the original study on the book-to-market effect (HML). We also follow McLean and Pontiff (2016) to determine the publication date by using the month and year on the cover of the journal publishing the original study. We use March 1981, March 1985, April 2013, and December 2004 for the publication dates of the original studies motivating SMB, HML, RMW, and CMA, respectively. We use February 1993 for the publication date of SMB and HML, and April 2015 for the publication date of RMW and CMA.

with some drawdown over the last year, its performance had been nearly flat over the decade up to the end of 2020. To illustrate post-publication return decay, Exhibit 1 also highlights the publication month and year of the original studies motivating each of the four factors and the month and year each factor was first published.[11]

Exhibit 2 also considers the month and year of the original studies and of the four factors and presents the average monthly returns, standard deviations, and *t*-statistics of the four factors for the full, pre-publication, and post-publication (including the month of publication) periods. For three of the four non-market factors, return premiums fell after publication. Although each of the four factors had a significantly

EXHIBIT 2

Average Monthly Returns of Fama–French Factors (%): Full Period, Pre-Publication, and Post-Publication

Panel A: Full Period (July 1963–March 2024; 729 months)

	SMB	HML	RMW	CMA
Average	0.20	0.29	0.28	0.27
Standard Deviation	3.04	3.00	2.22	2.08
t-Statistic	1.81	2.60	3.43	3.50

Panel B: Pre-Publication Period

	SMB	HML	RMW	CMA	SMB	HML	RMW	CMA
	Original Studies Motivating Fama–French Factors				Publication of Fama–French Factors			
Average	0.55	0.52	0.27	0.37	0.32	0.44	0.26	0.32
Standard Deviation	3.28	2.66	2.25	2.13	2.98	2.58	2.23	2.00
Number of Months	212	260	597	497	355	355	621	621
t-Statistic	2.46	3.15	2.96	3.89	2.03	3.23	2.94	3.94

Panel C: Post-Publication Period

	SMB	HML	RMW	CMA	SMB	HML	RMW	CMA
	Original Studies Motivating Fama–French Factors				Publication of Fama–French Factors			
Average	0.06	0.16	0.32	0.05	0.09	0.14	0.39	0.00
Standard Deviation	2.92	3.16	2.08	1.93	3.09	3.34	2.17	2.47
Number of Months	517	469	132	232	374	374	108	108
t-Statistic	0.46	1.09	1.79	0.38	0.57	0.82	1.87	0.00

NOTES: Following McLean and Pontiff (2016), we identify Banz (1981), Novy-Marx (2013), and Titman, Wei, and Xie (2004) as the publications first documenting the return predictability of size (SMB), gross profitability (RMW), and investment (CMA), respectively. We identify Rosenberg, Reid, and Lanstein (1985) as the original study on the book-to-market effect (HML). We also follow McLean and Pontiff (2016) to determine the publication date by using the month and year on the cover of the journal publishing the original study. We use March 1981, March 1985, April 2013, and December 2004 for the publication dates of the original studies motivating SMB, HML, RMW, and CMA, respectively. We use February 1993 for the publication date of SMB and HML, and April 2015 for the publication date of RMW and CMA. The month of publication is included in the post-publication period.

[11] Following the Internet Appendix of McLean and Pontiff (2016) (https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2Fjofi.12365&file=jofi12365-sup-0001-Table.pdf), we identify Banz (1981), Novy-Marx (2013), and Titman, Wei, and Xie (2004) as the publications first documenting the return predictability of size (SMB), gross profitability (RMW), and investment (CMA), respectively. However, we identify Rosenberg, Reid, and Lanstein (1985) as the original study on the book-to-market effect (HML), while McLean and Pontiff (2016) used Fama and French (1992) for that factor. We also follow McLean and Pontiff (2016) to determine the publication date by using the month and year on the cover of the journal publishing the original study. We use March 1981, March 1985, April 2013, and December 2004 for the publication dates of the original studies motivating SMB, HML, RMW, and CMA, respectively. And we use February 1993 for the publication date of SMB and HML, and April 2015 for the publication date of RMW and CMA.

positive return premium in the pre-publication period, no factor has delivered a statistically significant positive return (at the 5% level) after its publication, which reinforces the pattern of post-publication return decay seen in Exhibit 1.

Indeed, other research showed that for the decade from 2010 to 2019, each of the four Fama–French non-market factors had a realized return well below its long-term (47-year) average, with SMB and HML each producing a negative return.[12] The same research also showed, however, that many factors that are not part of the Fama–French five-factor model delivered positive premiums during this decade. These findings suggest, while the widely used Fama–French factors may lack consistency in performance, other factors may offer opportunities and diversification potential.[13] In other words, many smart beta investors are selecting exposures from a limited set of factors. Moreover, to achieve consistently positive returns, they would need to select the right factors at the right time.

Taken together, these findings suggest that passively relying on a limited set of factors that performed well historically may disappoint investors for extended periods. Instead, investors can benefit from an approach that is more active, dynamic, and provides diversification across multiple proprietary factors, as we discuss in the following.

FOCUSING ON SINGLE FACTORS

Smart beta portfolios that seek to exploit a single factor face two performance issues. First, they ignore the market's multidimensionality and its full range of return opportunities.[14] Second, they are highly prone to periods of poor performance by the selected factor.

To address these concerns, smart beta providers and investors have increasingly turned to two possible solutions: factor timing and factor diversification. But these approaches also have limitations. While some evidence suggests that tactical factor timing may be possible, conflicting evidence casts doubt on its efficacy.[15] Furthermore, factor timing is challenging in practice, and any successful factor-timing model is unlikely to be available to most investors.

Rather than attempt to time factors, investors can diversify exposures across multiple factors, hoping for a more stable, and perhaps more positive, portfolio return. After all, as some factors underperform, others may outperform. The concept of factor diversification is simple and intuitive and has spurred the growth of multifactor smart beta strategies in recent years.[16] Despite high expectations, however, many of these strategies have so far underperformed.[17]

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[12] See Blitz (2020).

[13] Such factors include low risk, price momentum, earnings momentum, analyst revisions, seasonality, and short-term reversal.

[14] See Jacobs and Levy (1988, 2014a).

[15] For evidence that factor timing may have potential, see, for example, Arnott et al. (2016), Hodges et al. (2017), Bender et al. (2018), and Fergis et al. (2019). For evidence questioning the effectiveness of factor timing as a practical strategy, see, for example, Asness et al. (2017) and Dichtl et al. (2019).

[16] According to FTSE Russell's smart beta survey of global asset owners (2019), 71% of survey respondents were using multifactor smart beta strategies in 2019, increasing from 49% in 2018. Furthermore, in 2019, multifactor strategies (78%) were the most commonly evaluated smart beta option among the asset owners; next in ranking came low volatility (42%) and value (40%). Invesco's recent report (2023), based on interviews with 130 systematic investors responsible for managing $22.5 trillion in assets as of March 2023, highlights a trend that most investors are expected to continue diversifying their factor exposures.

[17] For evidence on underperformance of multifactor strategies, see Estrada (2023) and Johnson (2020b). Aghassi et al. (2023) show empirically that a single factor can greatly affect the performance

Multifactor strategies remain susceptible to several of the fundamental limitations that afflict single-factor smart beta, despite offering more opportunity for diversification. They generally rely on only a small number of factors. They usually do not account for correlations between factors. And they typically do not attempt to adjust exposures for changes in underlying market and economic conditions. In the following, we compare smart beta with proprietary, dynamic, multifactor strategies (smart alpha) in terms of their ability to overcome these limitations.[18]

PARSIMONY VERSUS GREATER DIMENSIONALITY

Standard time-series factor models typically rely on a parsimonious design of a few, commonly up to five, factors. The equity market, however, is permeated with interrelated inefficiencies;[19] a handful of factors is hardly adequate to grapple with such a complex market. Because smart beta strategies typically build on standard factor models, they disregard many potential factors that could provide additional return opportunities and allow for greater diversification.

In contrast, smart alpha strategies can take fuller advantage of the market's multidimensionality by exploiting numerous fundamental and behavioral factors. They can do so because they adopt a cross-sectional approach to factor modeling that disentangles the unique contributions of each of numerous factors to the pricing of individual stocks.[20] This approach is distinct from the time-series approach underpinning smart beta, which relies on the average naïve returns over time of portfolios sorted on a few factors, one factor at a time. The concept of disentangling, which is especially important when comparing time-series and cross-sectional factors, is discussed next.[21]

TIME-SERIES VERSUS CROSS-SECTIONAL FACTORS

Time-series factors are conventional standalone factors that do not adequately control for the influence of other factors. Cross-sectional factors are constructed from cross-sectional regression and optimally isolate each factor from the effects of other factors.[22] While multifactor smart beta seeks exposure to a few simple time-series factors, smart alpha exploits numerous disentangled cross-sectional factors. Recent research has found that factor models based on cross-sectional factors provide greater explanatory power than models based on time-series factors.[23]

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of multifactor portfolios, as value did in the period 2018–2020, which partially explains why many multifactor strategies have failed to deliver tangible diversification benefits.

[18] See Jacobs and Levy (2014b).

[19] See Jacobs and Levy (1989a).

[20] See Jacobs and Levy (1988).

[21] See Jacobs and Levy (2021) for discussion of the practical benefits of the cross-sectional approach to factor modeling.

[22] Note that cross-sectional factor returns are measured at regular intervals, say, monthly or more frequently, resulting in a time series of factor returns for each cross-sectional factor.

[23] See Fama and French (2020). While their original factor portfolios (SMB, HML, RMW, and CMA) were constructed from simple portfolio sorts based on the corresponding time-series factors, the returns of the cross-sectional factor portfolios were estimated from a cross-sectional regression of stock returns on the firm characteristics corresponding to the time-series factors. Jacobs and Levy (2021) discuss two potential advantages of cross-sectional factors over time-series factors. First, time-series factors may not be optimally constructed because portfolio sorts are ad hoc; but cross-sectional factors are optimal because they are estimated from the regression of returns on prescribed characteristics. Second, time-series factors may inadvertently capture return effects from other related factors, while each cross-sectional factor is disentangled from the other factors considered simultaneously.

Because time-series factors do not account for cross-sectional correlations between factors, their historical return premiums can be misleading. Cross-sectional regression using individual stocks can control for cross-contamination and provide pure factor effects (Jacobs and Levy 1988). A simple combination of factor portfolios cannot make up for what time-series factors inherently lack.

As an example, consider the size and quality factors. When examined in isolation, the size effect appears to have faded since it was first documented in the early 1980s.[24] However, recent evidence shows that, after controlling for quality, the size premium reemerges as a robust factor: small stocks tend to outperform large stocks among firms of similar quality.[25] But a multifactor smart beta strategy that combines a small-size portfolio with a quality portfolio via a fixed weighting method will not capture the quality-adjusted size effect.[26] The combined portfolio ignores the negative correlation between small size and quality and ends up holding low-quality small stocks. In contrast, a cross-sectional smart alpha approach disentangles the size effect from the quality effect and other related effects, separating high-quality from low-quality small stocks. Smart alpha's pure factor returns are thus likely to be more predictive than the naïve returns of portfolios simply sorted on uncontrolled time-series factors.

STATIC VERSUS DYNAMIC DESIGN

Smart beta is typically a static strategy by design, regardless of whether it seeks exposure to a single factor or multiple factors. It offers rules-based portfolio construction designed to provide exposure to targeted factors, with rebalancing at predetermined intervals. The rules are typically set out during the design phase of smart beta, rather than as part of the ongoing investment process. As a result, smart beta performance tends to be vulnerable to changing market conditions.

In contrast, smart alpha is dynamic. It derives the time series of disentangled factor returns from cross-sectional regression and can use this analysis to forecast pure returns to each factor while considering market and economic conditions.[27] These pure returns can be combined with the observed values of each firm's characteristics to obtain the predicted return for each stock. Thus, smart alpha actively monitors factor performance as conditions change and makes necessary adjustments to factor selection and factor exposures based on ongoing proprietary research. After all, outperforming the market requires developing insights that are not known by market participants generally.

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[24] See, for example, Schwert (2003) and McLean and Pontiff (2016).

[25] See Asness et al. (2018). They provide evidence that illustrates the difference between time-series and cross-sectional factors; the original size factor with no quality adjustment is a time-series factor and the size factor with a quality adjustment is a cross-sectional factor.

[26] There are two approaches to construction of multifactor smart beta portfolios: top-down and bottom-up. The top-down approach builds a multifactor portfolio by combining multiple *single*-factor portfolios. The bottom-up approach builds a portfolio by selecting and weighting individual stocks based on multiple factors. Bender and Wang (2016) documented that the bottom-up approach produces better results than the top-down approach because the latter does not capture the interaction effects among factors. Note, however, that even their bottom-up approach does not optimally control each factor for the influence of other factors because stock selection and weighting are simply based on the average rank across multiple factors.

[27] See Jacobs and Levy (1989b).

CONCLUSION

Smart beta promised to deliver consistent excess returns relative to the broader market with more transparency and lower fees than active alternatives. As a result, it has surged in popularity in the past decade. But smart beta factor returns have fluctuated as market conditions changed over time, and many smart beta strategies have underperformed the market for extended periods. This is hardly surprising considering the limitations of the parsimonious factor pricing models underpinning smart beta. The transparency and popularity of smart beta factors also make their returns more prone to being arbitraged. The disparity between promise and performance has led smart beta providers and investors to explore ways to make smart beta work in different market environments by timing factors and seeking exposure to multiple factors.

Such efforts, of course, move smart beta away from the discipline of passive investing (at the cost of less transparency and higher fees), a natural progression for smart beta to become smarter. Smart beta and “smarter beta” are unlikely to succeed, however; being smarter is not sufficient to unravel the intricacies of security pricing. It takes an intensive, proprietary empirical analysis of security pricing to gain an informational edge.

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