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Smart Beta Exchange-Traded Funds and Factor Investing

It was early 2015 and executives in the iShares Factor Strategies Group were considering the launch of some new exchange-traded funds (ETFs). The new ETFs were in a class of ETFs called smart beta funds. Most traditional ETFs' portfolio weights were based on the market capitalization of a stock (stock price times the number of outstanding shares), but smart beta ETFs' weighting schemes were based on firms' financial characteristics or properties of their stock returns.

iShares was a division of BlackRock, Inc., an international investment management company based in New York. In 2014, BlackRock was the world's leading asset manager, with over $4.5 trillion in assets under management.[1] In 2014, iShares globally offered over 700 ETFs with almost $800 billion in net asset value in the US and $1 trillion globally—a 39% market share, making iShares the largest issuer of ETFs in the world.[2]

The new smart beta multifactor ETFs being considered by iShares would provide investors with simultaneous exposure to four fundamental factors that had shown themselves historically to be significant in driving stock returns: the stock market value of a firm, the relative value of a firm's financial position, the quality of a firm's financial position, and the momentum a firm's stock price has had. While each of these factors existed in different combinations and different forms in ETFs already in the marketplace, no firm was currently offering these four as a combination in a multifactor ETF. The executives at iShares were unsure whether there would be demand in the marketplace for such multifactor ETFs, since their value added from an investor's portfolio perspective was unknown.

Factors

Smart beta portfolios were driven by academic research that shows there is a common set of driving forces, or factors, that consistently explains stocks' average returns and systematic risks. Professors Eugene Fama and Kenneth French have been at the forefront of developing factor models, having written a series of papers examining different financially based factor models of stock returns. As the culmination of their decades of research, in 2013 Fama and French introduced a model that showed a systematic relationship between the average returns of stocks and five underlying factors.[3]

Based on the capital asset pricing model (CAPM) theory, the first factor Fama and French considered was the relative covariance of a firm's stock returns with a market portfolio. The CAPM theory states that stock return movements can be broken down into two components: movements due to the returns of an underlying market portfolio (a *market factor*) and firm-specific movements, with a stock's average returns determined by its co-movements with the market portfolio. This can be seen via the CAPM's factor model:

$$r_{i,t} - r_f = \alpha_i + \beta_i \left(r_{m,t} - r_f \right) + \varepsilon_{i,t} \tag{1}$$

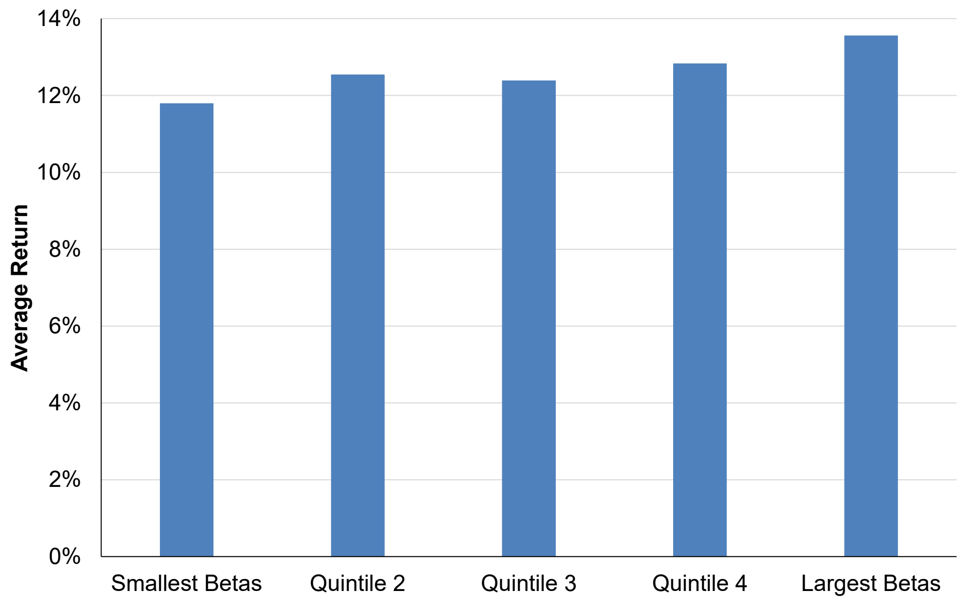
where $r_{i,t}$ is the return at time t for some security i, r_f is the return to a risk-free asset, α_i and β_i are regression coefficients, $r_{m,t}$ is the return to a market portfolio (the market factor) at time t, and $\varepsilon_{i,t}$ is the regression's residual. A stock's co-movement with the market portfolio is measured by its CAPM beta (β_i), the regression coefficient above.

Figure 1 shows the average returns on five portfolios ranked by the size of their betas using annual data from 1964 through 2014. These portfolios were created by sorting all stocks listed on the NYSE, AMEX, and NASDAQ by their betas and then splitting the stocks into quintile portfolios based on the level of their beta, with those stocks with betas in the bottom 20% of the distribution put into a smallest beta quintile portfolio, then the next 20% into the next highest quintile portfolio, and so on. Figure 1 shows no evidence of a strong upward sloping relationship between a portfolio's beta and its average return, contrary to the prediction of the CAPM theory. Thus, Fama and French concluded that the CAPM theory does not explain average returns very well.*[4]

The second factor Fama and French explored was the size of a firm as measured by its market capitalization, what is termed a *size factor*. Fama and French (and others) found a significant negative relationship between the size of a firm and its average return—that is, firms with small market capitalizations earn higher average returns across time than firms with large market capitalizations. **Figure 2** plots the average returns of portfolios grouped into quintiles by their market capitalizations. What we see in Figure 2 is the small firm effect; small firms have higher average returns than large firms, with a consistent rise in average returns as we go from the smallest to the largest firm's portfolio.

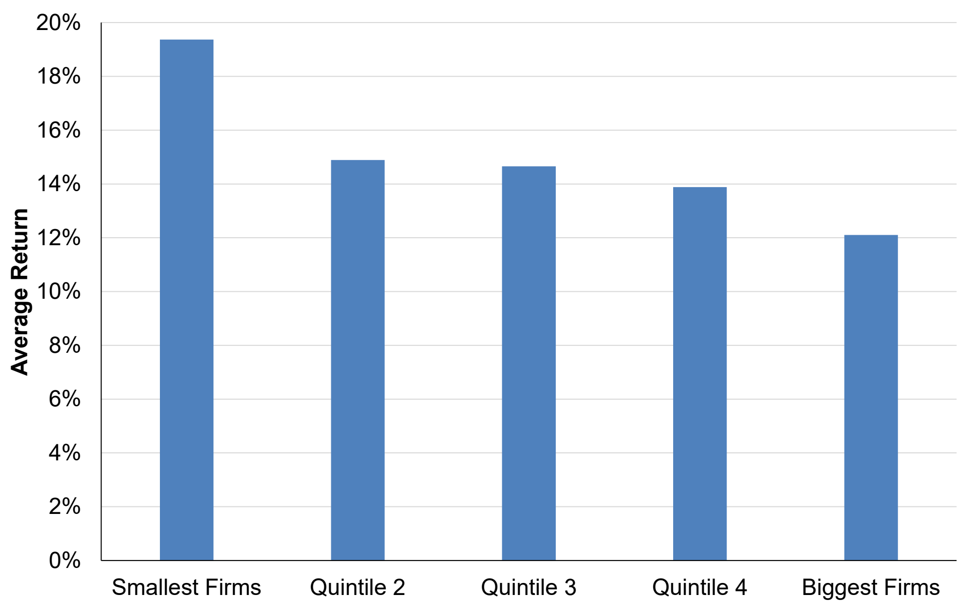
* Note that Fama and French used a longer time frame, from 1927–1990, to construct the portfolios in this study than were used to construct the portfolios in Figure 1 (1964–2014).

Figure 1: Relationship Between Average Returns and the CAPM Beta



Source: Author's calculations using data from Ken French's data library, accessed August 2016, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. These portfolios are from French's univariate portfolios, sorted by beta, using annual value-weighted data from 1964–2014.

Figure 2: Relationship Between Average Returns and Firm Size

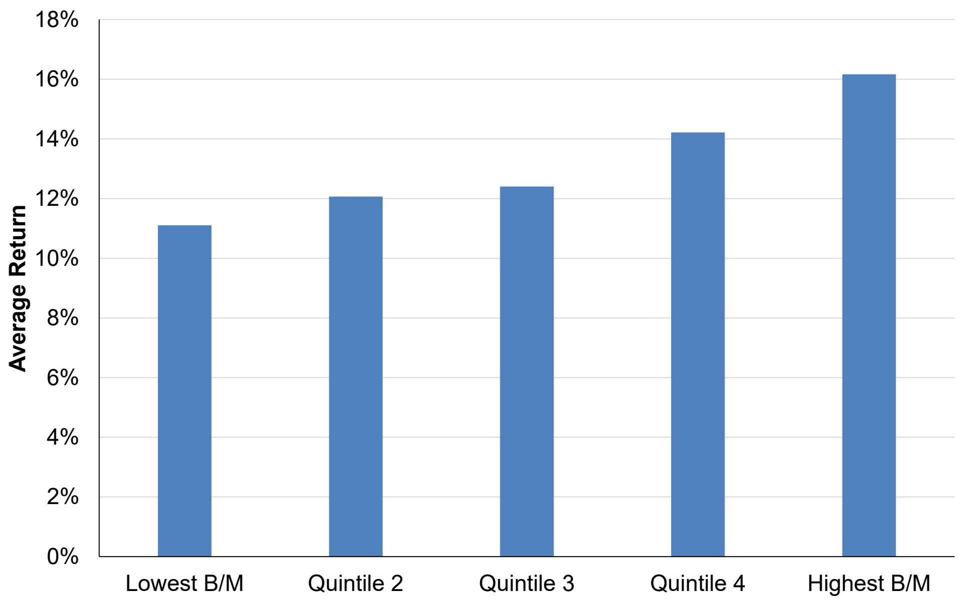


Source: Author's calculations using data from Ken French's data library, accessed August 2016, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. These portfolios are from French's univariate portfolios, sorted by firm size (market capitalization), using annual equal-weighted data from 1964–2014.

At first glance it is not obvious why smaller firms should have higher average returns. Fama and French showed that, controlling for other factors, size is related to a firm's profitability; small firms have lower earnings on assets than big firms.[5] Firm size is also thought to proxy for specific risk factors associated with smaller firms; researchers have explored the underlying sources of such risks, but the results are not conclusive. Some have argued that because small firms' stocks do not trade as often as larger firms and are thus less liquid, investors in smaller firms require higher returns for accepting this liquidity risk.[6] Others suggest that size is correlated with information uncertainty—that is, smaller firms are not often followed by investment banks while simultaneously having more volatile fundamentals.[7]

The third factor that Fama and French considered was a *value factor*, which is the ratio of a firm's book value (as given by a firm's balance sheet, its assets minus its liabilities) to its market capitalization—its book-to-market (B/M) ratio.[8] **Figure 3** plots the average returns of five portfolios that were created by ranking stocks by their B/M ratio and then sorting them into quintile portfolios from low B/M ratios to high. What we see in Figure 3 is that the portfolios with higher B/M ratios have higher average returns, which is termed a value effect.

Figure 3: Relationship Between Average Returns and the Book-to-Market Ratio

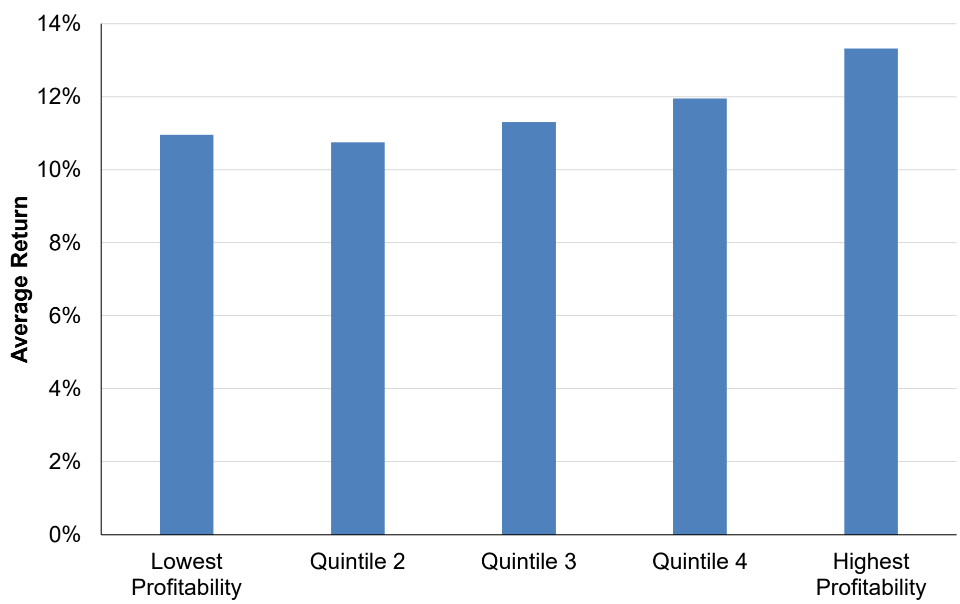


Source: Author's calculations using data from Ken French's data library, accessed August 2016, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. These portfolios are from French's univariate portfolios, sorted by the B/M ratio, using annual value-weighted data from 1964–2014.

Fama and French argue that this positive relationship between average returns and B/M ratios is because high B/M stocks are less profitable and are relatively distressed, so these firms are riskier and have higher average returns to reflect that. Conversely, low B/M firms have high returns on capital with sustained profitability (hence they are termed growth stocks); therefore, they are less risky and have lower average returns. The B/M effect is called a value effect because "When a firm's market value is low relative to its book value, then a stock purchaser acquires a relatively large quantity of book assets for each dollar spent on the firm. When a firm's market price is high relative to its book value the opposite is true."[9]

The fourth factor that Fama and French proposed was a profitability factor, the ratio of a firm's operating profit to its book value.* In **Figure 4**, the average returns of five portfolios are presented, sorted from low to high profitability. To create these portfolios, firms were ranked by the Fama and French profitability measure and then sorted into quintile portfolios. As can be seen in Figure 4, more profitable firms earn significantly higher average returns than less profitable firms. The argument is simply that firms with productive assets should have higher returns than firms with unproductive assets. This profitability factor is sometimes referred to as a *quality factor*—firms with higher profitability are higher quality firms. "While traditional value strategies finance the acquisition of inexpensive assets by selling expensive assets, [a quality strategy] exploits a different dimension of value, financing the acquisition of [quality] productive assets by selling unproductive assets."[10]

Figure 4: Relationship Between Average Returns and Profitability



Source: Author's calculations using data from Ken French's data library, accessed August 2016, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. These portfolios are from French's univariate portfolios, sorted by profitability, using annual value-weighted data from 1964–2014.

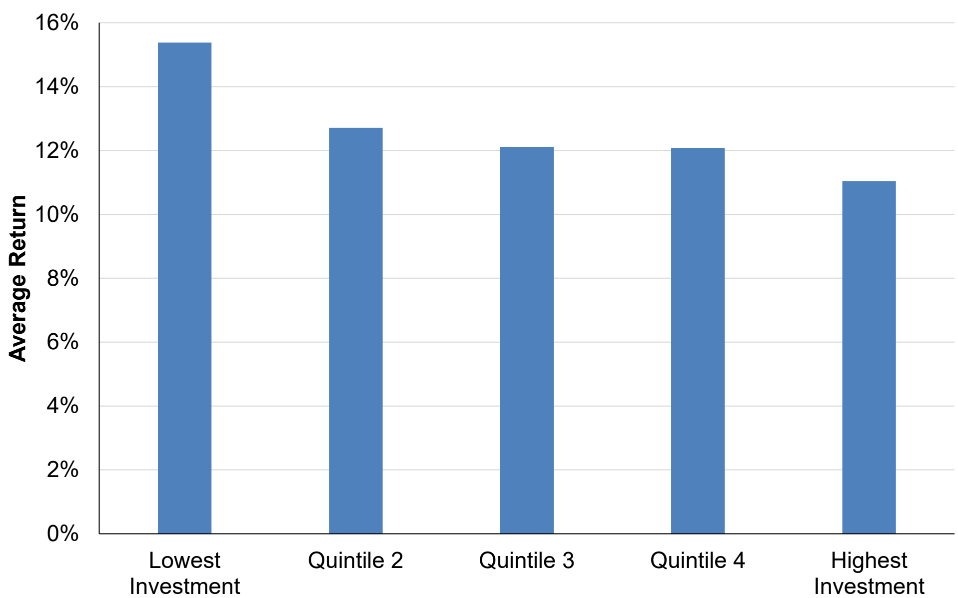
The fifth Fama and French factor was an investment factor, which they measured as the percentage change in the value of a firm's assets over the course of a year.[11] In **Figure 5**, firms are ranked by this investment measure and then sorted into quintile portfolios, from conservative (low

* Fama and French's measure of operating profit is a firm's revenues minus costs of goods sold, minus selling, general, and administrative expenses, minus interest expense.

levels of investment) to aggressive (high levels of investment). As shown in Figure 5, portfolios with conservative levels of investment have higher average returns than aggressive firms.

Fama and French's rationale for this investment effect is that, holding a firm's expected revenues constant, a rise in a firm's investment implies lower future expected earnings and thus lower expected returns, while lower investment levels yield higher expected earnings and thus higher expected returns. Like the profitability factor, the investment factor is also termed a *quality factor* because firms with lower levels of investment are higher quality firms because they are not depressing their earnings via excessive investment and are putting less stress on their balance sheets.

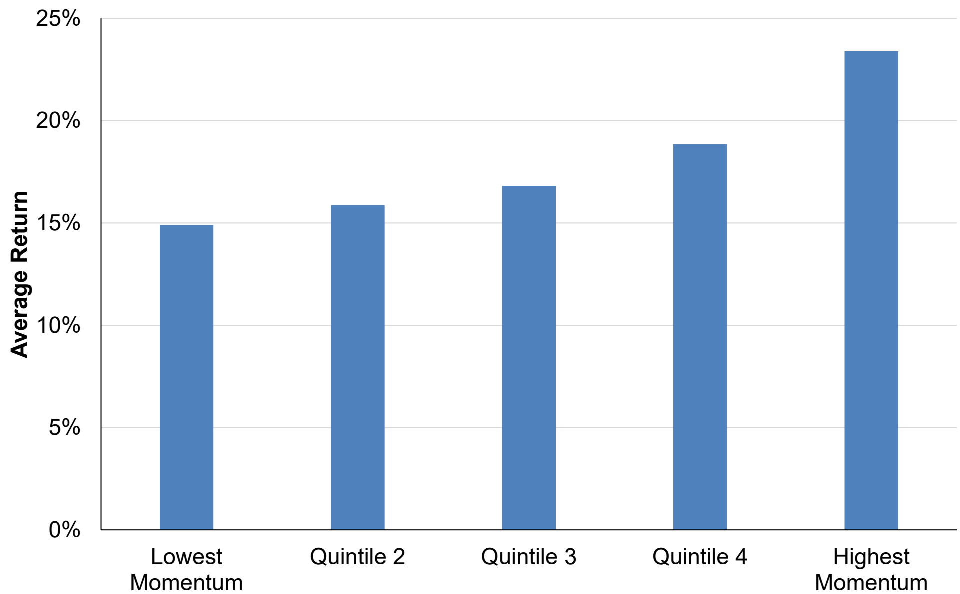
Figure 5: Relationship Between Average Returns and Investment



Source: Author's calculations using data from Ken French's data library, accessed August 2016, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. These portfolios are from French's univariate portfolios, sorted by investment, using annual value-weighted data from 1964–2014.

Separately from Fama and French, a series of authors have examined what is termed a *momentum factor*.[12] The momentum effect documents that stocks that have large price appreciation in one year continue to have high price appreciation the following year and stocks with negative or low price appreciation continue to do so the following year. In **Figure 6**, stocks are sorted into quintile portfolios based on their stock price appreciation in the previous year, from those stocks that performed in the bottom 20% of all stocks in the previous year, what is termed a loser portfolio, to stocks that performed in the top 20% over the last year, a portfolio of winners. As Figure 6 shows, the greater the price appreciation for a portfolio over the last year, the higher that portfolio's average return.

Figure 6: Relationship Between Average Returns and Momentum



Source: Author's calculations using data from Ken French's data library, accessed August 2016, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. These portfolios are from French's univariate portfolios, sorted by momentum, using annual equal-weighted data from 1964–2014.

In a recent study, Fama and French found that, after controlling for the market, size, value, profitability, and investment factors, a momentum factor had no significance in determining average returns.[13] Others, however, find their evidence inconclusive, and continue to see a relevance for a momentum factor even after these other factors are controlled for.[14]

There are two schools of thought as to why we see a relationship between a stock or portfolio's momentum and its average returns: the rational "markets are efficient" school and the behaviorist "markets are inefficient" school. A rational market perspective on the causes of the momentum effect would hold that firms with high momentum face greater cash flow risks and/or higher discount rates because of the nature of their investment sets.[15] The behaviorists view the momentum effect as resulting from investors' cognitive biases. For example, investors who choose to invest in a high-return stock are simply extrapolating past performance into the future, exhibiting a kind of herding behavior.[16]

To understand how factors are a set of driving forces across financial securities' returns, the next step is to consider an actual factor model. A factor model is a regression that relates securities' returns to a set of factor portfolios. For example, the CAPM theory implies that there is only one factor driving security returns, the market portfolio. Given this, equation (1) is the CAPM's factor model. For the six factors just discussed, the factor model would be a six-factor regression model of the form:

$$r_{i,t} - r_f = a_i + b_i\left(r_{m,t} - r_f\right) + s_i(F_{Size,t}) + h_i(F_{B/M,t}) + r_i(F_{Profitabilty,t}) + c_i(F_{Investment,t}) + m_i(F_{Momentum,t}) + \varepsilon_{i,t} \quad (2)$$

where $r_{i,t}$ is again the return on some stock, $r_{m,t}$ is the return on the market, r_f is the return to a risk-free asset, $F_{Size,t}$ through $F_{Momentum,t}$ are the factor portfolios for each of the other five variables discussed above, a_i is the regression intercept, b_i to m_i are the regression slope coefficients, and $\varepsilon_{i,t}$ is the regression's error term. From this regression you can see that this six-factor model is the CAPM shown in equation (1) plus five additional factors.

The factor portfolios, $F_{Size,t}$ through $F_{Momentum,t}$, can be created in different ways. A simplified example of one standard approach is to use the decile portfolios with the highest average return for a particular variable—for example, the decile with the smallest firms would be used for the size factor portfolio, $F_{Size,t}$; and the decile with the highest B/M ratios would be used for the B/M or value factor portfolio, $F_{B/M,t}$, and so on. These factor portfolios are called long-only portfolios because they only include purchases of stocks in the portfolio.

An example of a second standard approach, following Fama and French's work, is to use a long-short factor portfolio. Simplistically, a long-short factor portfolio is constructed by taking the returns on the decile with the highest average return less the returns on the decile with the lowest average return. It is called long-short because the portfolio includes both purchases (long) as well as shorts—you short a security by borrowing the security from a broker and then selling it. For example, using this approach the size factor portfolio, $F_{Size,t}$, would be the returns to the decile with the smallest firms less the returns to the decile portfolio with the biggest firms.* Fama and French call this the SMB portfolio, for small firms minus big firms. Fama and French's other long-short portfolios for their five-factor model are:

- HML (high minus low): The returns of the decile portfolio that includes the firms with the highest B/M ratios less the returns to the decile portfolio with the lowest B/M ratios.
- RMW (robust minus weak): The returns of the decile portfolio that includes the firms with the most robust profitability less the returns to the decile portfolio with the weakest profitability.
- CMA (conservative minus aggressive): The returns of the decile portfolio that includes the firms with the lowest (most conservative) levels of investment spending less the returns to the decile portfolio with the highest (most aggressive) investment spending.

Background on Smart Beta ETFs

The intent behind smart beta ETFs is to capture the high expected returns identified for factors in the work of Fama and French and others.[17] The term "smart beta" is a fairly new marketing

* This simplifies what Fama and French actually do, which is to take the bottom 30% of firms in market size for the small firm portfolio and the top 30% of firms in market size for the big firm portfolio. This is also true for the other Fama-French long-short portfolios defined in the case.

identifier; some of the alternative names that have been used include strategic beta, active beta, enhanced index, alternative beta, and scientific beta. There is no one specific definition of what a smart beta portfolio is. However, a common theme across definitions is that smart beta portfolios are constructed such that the emphasis is weighting stocks in these portfolios not on the traditional measure of market capitalization, but by incorporating into their weighting scheme some aspect of a security's fundamental value, such as a stock's B/M ratio, profitability, or a characteristic of the security's performance, such as a stock's momentum.* Regardless what definition is used for smart beta ETFs, the bottom line is that they are proxies for the factor portfolios, the $F_{i,t}$'s, that we discussed in the previous section.

Smart beta ETFs are considered a combination of passive and active investing. The funds are passive because they passively mimic what are termed factor indexes and hence do not require any input from a portfolio manager. They are considered active because their weights deviate from standard market capitalization weights. As Cliff Asness, a founder, managing principal, and chief investment officer at AQR Capital Management, a global investment management firm that has been at the forefront in creating momentum factor portfolios, has stated, "A portfolio that deviates from market weights . . . must be balanced by other investors who are willing to take the other side of those bets. For example, for every value investor, who tilts toward or selects cheap value stocks, there must be an investor on the other side who is underweighting value and overweighting expensive, growth stocks. Hence, as everything must add up to the market-weighted portfolio, everyone at once cannot hold or tilt toward value at the same time."[18] Smart beta portfolios are not active in the sense that fund managers are searching for mispriced securities. Although some justify smart beta portfolios from the behaviorist perspective that the factors are mispriced,[19] it is not necessary to use this justification to motivate smart beta strategies.[20]

Besides smart beta ETFs that capture the size, value, quality, and momentum factors we have discussed, there are also dividend, minimum-volatility, and other factor-based smart beta stock ETFs, as well as bond ETFs that capture factors specific to bonds. Dividend ETFs in general try to capture potentially higher average returns from investing in stocks paying high dividends.[†21] The rationale for minimum-volatility (also called low volatility) ETFs is the documented evidence that stocks with low volatility or risk have higher average returns than high volatility stocks.[22] There is also a class of multifactor ETFs, whose goal is to provide exposure to a set of two or more factors simultaneously.

In 2014, mutual funds that mimic underlying factors had existed for a while, but smart beta ETFs were newer to the marketplace.[‡] **Figure 7** shows the level of assets under management in

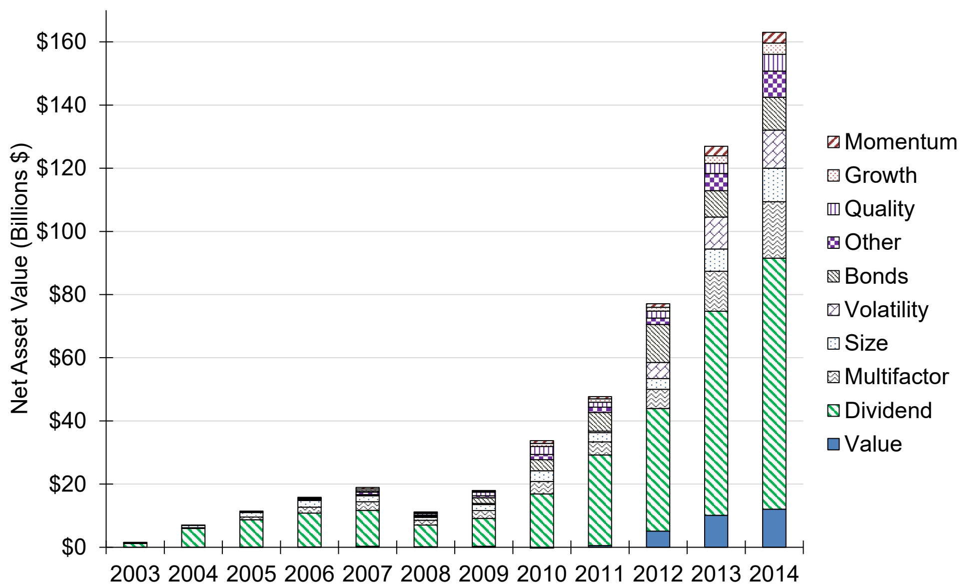
* This is not a strict definition, however; some firms classify traditional value, growth, dividend, and small firm portfolios whose weighting scheme uses market capitalization weights into the smart beta category, while other firms do not.

† Note that Fama and French consider the B/M ratio and their profitability measure to be better predictors of average returns than the dividend yield; see https://famafrench.dimensional.com/questions-answers/qa-dividends-is-bigger-better.aspx, accessed January 2018.

‡ The market statistics in this section are the author's calculations using data from the Center for Research in Security Prices and a partial list of ETFs from http://www.etf.com, accessed September 2016. Note that the group of smart beta ETFs included in this analysis excludes traditional value, growth, dividend, and small firm portfolios whose weights are based on market capitalizations, which ETF.com classifies as smart beta.

smart beta ETFs listed in the US from 2003, when the first smart beta ETFs were introduced, through 2014. The smart beta market grew from around $1.5 billion in 2003 to just over $160 billion at the end of 2014, a cumulative annual growth rate of 47%.* Figure 7 also shows the breakdown of assets under management by smart beta category, with dividend ETFs having the most assets under management and momentum ETFs with the least. **Figure 8** shows the number of smart beta ETFs and their share of the overall US ETF market. In 2003, there were only six smart beta ETFs; this had grown to 277 by 2014. In 2003, smart beta ETFs were 1% of the overall US ETF market and this grew to an 8% market share by 2014.

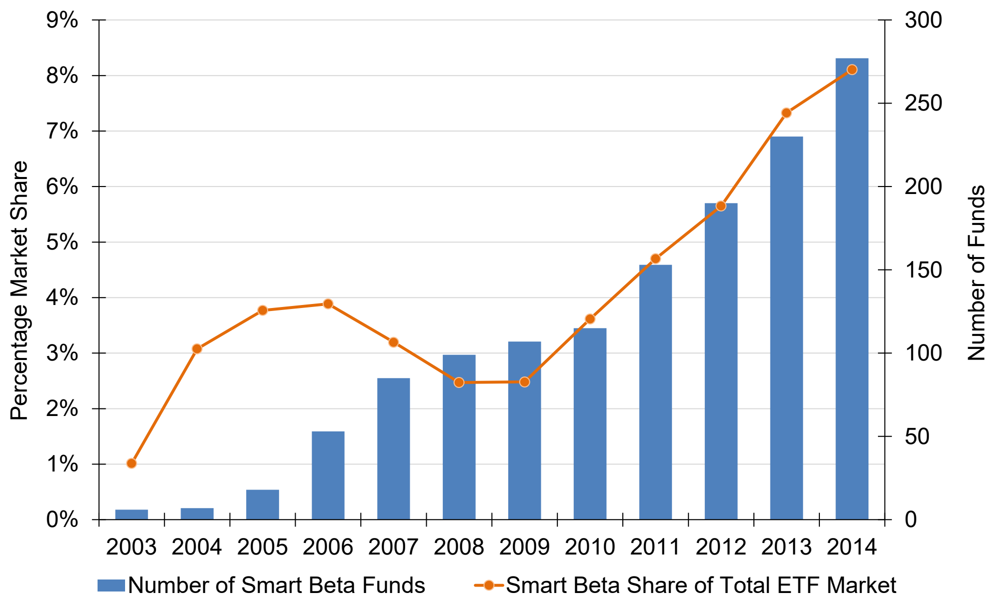
Figure 7: Market Size and Breakdown for US Smart Beta Exchange-Traded Funds



Sources: Author's calculations using data from the Center for Research in Security Prices and a partial list of smart beta ETFs from http://www.etf.com. Note that the group of smart beta ETFs in the analysis excludes traditional value, growth, dividend, and small firm portfolios whose weights are based on market capitalizations.

* If traditional market capitalization–based value, growth, and small firm ETFs are included in the analysis, the smart beta market size in 2014 was $360 billion.

Figure 8: Number of US Smart Beta Exchange-Traded Funds and Market Share Relative to Total US ETF Market



Sources: Author's calculations using data from the Center for Research in Security Prices and the list of ETFs from http://www.etf.com. See the source notes to Figure 7 for more detail.

In 2014, iShares had a 38% overall US ETF market share and a 22% share of the smart beta market. Its closest competitor, State Street Corporation, had a 23% overall ETF market share, but only a 10% smart beta market share. The other major player in the smart beta market was Invesco PowerShares Capital Management, which had a 15% smart beta market share, but only a 5% overall ETF market share. The Vanguard Group had a 21% overall ETF market share but offered no smart beta ETFs.*

At the end of 2014, iShares offered 19 different smart beta ETFs in the US with $36 billion in assets under management. A list of these ETFs is presented in **Table 1**, along with their net asset values. iShares introduced its first dividend ETF in 2003, the iShares Select Dividend ETF (DVY), and by 2014, iShares offered a range of smart beta ETFs, both international and domestic US, for equities as well as bonds. In 2013, iShares introduced four smart beta ETFs directly related to the research of Fama and French and others: its size, value, quality, and momentum factor ETFs.

* Vanguard did not sell smart beta funds because it questioned the value the approach added for investors. See, for example, C. B. Philips et al., "An Evaluation of Smart Beta and Other Rules-Based Active Strategies," Vanguard Research (2015). Vanguard did, however, offer a variety of capitalization-weighted ETFs similar to smart beta ETFs, such as its dividend appreciation ETF (VIG), its value ETF (VTV), and its small cap ETF (VB).

Table 1: List of Smart Beta ETFs Sold by iShares in 2014

Name	Ticker	Net Asset Value ($ in millions)
iShares Asia/Pacific Dividend ETF	DVYA	55
iShares Core Dividend Growth ETF	DGRO	152
iShares Core High Dividend ETF	HDV	5,197
iShares Edge MSCI Min Vol Asia ex Japan ETF	AXJV	5
iShares Edge MSCI Min Vol EAFE ETF	EFAV	1,356
iShares Edge MSCI Min Vol Emerging Markets ETF	EEMV	1,907
iShares Edge MSCI Min Vol Europe ETF	EUMV	4
iShares Edge MSCI Min Vol Global ETF	ACWV	1,561
iShares Edge MSCI Min Vol Japan ETF	JPMV	10
iShares Edge MSCI Min Vol USA ETF	USMV	3,581
iShares Edge MSCI USA Momentum Factor ETF	MTUM	482
iShares Edge MSCI USA Quality Factor ETF	QUAL	721
iShares Edge MSCI USA Size Factor ETF	SIZE	213
iShares Edge MSCI USA Value Factor ETF	VLUE	517
iShares Emerging Markets Dividend ETF	DVYE	213
iShares International Select Dividend ETF	IDV	4,163
iShares MSCI USA Equal Weighted ETF	EUSA	62
iShares Select Dividend ETF	DVY	15,554
iShares Yield Optimized Bond ETF	BYLD	9

Sources: Center for Research in Security Prices and http://www.etf.com. Note that traditional market capitalization–weighted portfolios are excluded from this analysis.

The multifactor ETFs that iShares was considering would be a combination of the size, value, quality, and momentum factors together, encompassing both international and domestic US stocks. As shown in Figure 7, multifactor ETFs only had $40 million in net asset value in 2003, which grew to $18 billion by 2014, a 76% cumulative annual growth rate. Prior to 2013, all the multifactor ETFs in the market captured just two effects, combining the size effect with one of the other factors. The type of multifactor ETFs that iShares was considering, which capture three or four factors simultaneously, was very new to the market. At the end of 2014, only three firms offered such multifactor products in the US market, with a combined net asset value of only about $150 million.[*23]

* A small competitor, WisdomTree Investments Inc., introduced a multifactor ETF based on the size, quality, and dividend factors in 2013, the WisdomTree US Small Cap Quality Dividend Growth Fund (DGRS), which at the end of 2014 only had a market value of $25 million. In mid-2014, State Street offered a set of 12 international multifactor ETFs, its SPDR MSCI Quality Mix ETF suite, and had announced the release of a US multifactor ETF for early 2015. These MSCI Quality Mix ETFs combined the value, low volatility, and quality factors into one ETF; at the end of 2014, this group of ETFs only had a total market value of $66 million. J. P. Morgan Asset Management introduced two multifactor ETFs in 2014: the JPMorgan Diversified Return Global Equity ETF (JPGE) and the Diversified Return International Equity ETF (JPIN), which brought together the size, value, momentum, and volatility factors and combined had around $60 million market value at the end of 2014.

Smart Beta Construction Methodology

A critical aspect of smart beta portfolios is that the portfolio construction methodology is rule-based, transparent, and low-cost to implement,[24] thus ensuring that the portfolios fit within the standard structure of passive ETFs. No common construction methodology is used across the smart beta ETFs sold by different firms—each uses different financial variables and methods of calculating weight. Because of this, the performance of different smart beta ETFs with the same objective can diverge.

Perhaps the easiest way to understand the essence of how smart beta portfolios are created is to consider the smart beta index construction methodology pioneered by Research Affiliates, an institutional investment advisor and manager and a pioneer in the development of smart beta indexes and portfolios, called fundamental indexing.[25] Given a financial variable, such as book value, the fundamental indexing approach determines the weight for each stock in an index via the formula:

$$w_{i,j} = \frac{F_{i,j}}{\sum_{i=1}^{N} F_{i,j}} \tag{3}$$

where $w_{i,j}$ is the fundamental weight for some security i for some financial variable j, $F_{i,j}$ is the value of the financial variable j (such as book value) for firm i and N is the number of securities in the sample.

Often smart beta ETFs use more than one financial variable in their construction. For example, Research Affiliates uses sales, cash flow, dividends, and book value to create its RAFI Value Factor US Index.[26] To accomplish this, the weights for each financial variable j from above are averaged across all the financial variables used to define the index and then re-standardized.

The methodology that iShares used in constructing its size, value, quality, and momentum factor ETFs was developed by MSCI Inc., a New York–based financial services firm known for its indexes, performance reporting, and risk management tools. The following iShares smart beta ETFs were indexed to the following MSCI factor indexes:

- The iShares Edge MSCI USA Size Factor ETF (SIZE) was indexed to the MSCI USA Risk Weighted Index,* in which the weights were determined by the risk of the underlying stocks.[27]
- The iShares Edge MSCI USA Value Factor ETF (VLUE) was indexed to the MSCI USA Enhanced Value Index, in which the weights were calculated using three valuation characteristics: the forward price-to-earnings ratio, the enterprise value to operating cash flow ratio, and the price-to-book ratio (the inverse of B/M).[28]

* Note that the iShares size factor ETF is not a traditional small firm portfolio because the weights in the portfolio are determined by the risk of a stock, not its market capitalization.

- The iShares Edge MSCI USA Quality Factor ETF (QUAL) was indexed to the MSCI USA Quality Index, which used the variables return on equity, debt to equity, and earnings variability to determine its stock weightings.[29]
- The iShares Edge MSCI USA Momentum Factor ETF (MTUM) was indexed to the MSCI USA Momentum Index, which used a stock's returns for the previous 6 to 12 months, standardized by the stock's volatility, to estimate the stock weightings.[30]

In constructing their factor indexes, MSCI assigns each stock in their sample what is called a Z-score. The Z-score is a statistic based on where a firm's valuation characteristic (e.g., its price-earnings ratio) lies relative to the mean of the valuation characteristic for the sample of stocks used, standardized by the standard deviation of the valuation characteristic across the sample. Specifically,

$$z_{i,j} = \frac{F_{i,j} - \mu(F_j)}{\sigma(F_j)} \tag{4}$$

where $z_{i,j}$ is the Z-score, $F_{i,j}$ the financial variable j under consideration for firm i, $\mu(F_j)$ is the mean of financial variable j for all stocks in the sample, and $\sigma(F_j)$ is the standard deviation of that financial variable across all stocks in the sample. Z-scores have an advantage over fundamental indexing because they consider not just the mean of the underlying financial variable, but also the dispersion of the underlying financial variable. You can interpret a Z-score as a measure of how many standard deviations a financial variable is from its mean.

MSCI also uses multiple financial variables in defining its indexes. As mentioned above, for example, its MSCI USA Enhanced Value Index uses the forward price-to-earnings ratio, the enterprise value to operating cash flow ratio, and the price-to-book ratio. To get the weight for a security in its Enhanced Value Index, an individual Z-score is calculated for each of the three financial variables used to construct the index and then a composite Z-score is calculated as the average of the individual Z-scores across the financial variables j from above, and then re-standardized.[31]

The multifactor ETFs that iShares was considering would be constructed using the methodology of MSCI's diversified multifactor indexes. MSCI produced these indexes for international markets as well as the US, for both large-mid-cap stocks and small-cap stocks. MSCI planned to introduce these indexes in early 2015[32] and iShares was considering offering ETFs to coincide with their introduction. Corresponding to the MSCI indexes, iShares was considering introducing five multifactor ETFs: a US large-mid-cap, a US small-cap, an international large-mid-cap (excluding US), a global large-mid-cap (including US), and an international small-cap. In creating its diversified multifactor indexes, MSCI assigned a weight to each stock that was an average of the stock's individual Z-scores for the size, value, quality, and momentum indexes.*

* MSCI's size weighting scheme for its multifactor index was different than that used to create its risk weighted index, which was used by iShares to create its size ETF. In the multifactor indexes a stock is assigned a size weight based on the inverse of the log of a stock's market capitalization (rather than a stock's risk, as in the risk weighted index). Note that once each stock is assigned an overall Z-score, the index is optimized to match the standard deviation of MSCI's USA Index.

MSCI's multifactor indexes were constructed differently than the multifactor ETFs already in the marketplace. These other multifactor ETFs were constructed by averaging the underlying single-factor indexes, a top-down approach. MSCI used a bottom-up approach, weighting each stock in the multifactor index by the set of its fundamental valuation characteristics, the Z-scores. Alain Dubois, head of new business and product development in the index unit at MSCI, claimed that the bottom-up approach taken by MSCI's indexes "will optimize the exposure to these factors to a greater degree than [the top-down approach]."[33]

Factor Investing

Everyone has heard that they should hold a well-diversified portfolio, but the question is, how should one diversify one's portfolio? A standard method is to diversify investments by asset class—that is, investing some in equities, some in bonds, some in real estate, some in commodities, and so on. Factor investing offers an alternative method to implement a diversification strategy. With factor investing you diversify your portfolio across factor portfolios (smart beta ETFs) so that your investments will have some amount in a small firm portfolio, some in a value portfolio, some in a quality portfolio, and so on. As described in iShares promotional material, "Smart beta strategies are the 'gateway' to factor investing—designed to harvest broad, persistent drivers of returns by taking advantage of economic insights, diversification, and efficient trading execution."[34]

The intuition behind factor investing is that a standard diversification strategy that emphasizes asset classes may not have the optimal exposures to the factors that are known to yield high average returns across time. Moreover, since diversification is also about the correlation structure across investments, factor investing can also help maximize diversification by providing a richer set of cross-correlations and thereby better manage the risk and return of a portfolio across market cycles.[35] This is because the returns and risks between factor portfolios vary relative to each other across changing business conditions while traditional asset class market capitalization stock portfolios' returns and risks move more closely together. For example, the returns and risks of size and value factors are highest in the early part of an economic expansion, while momentum and quality factors are highest at the beginning of an economic contraction.[36] Furthermore, quality and momentum factors outperform in declining interest rate environments, while value and size outperform with rising rates.[37] These findings indicate that the return and risk of a factor investment portfolio are managed by bringing the different cyclicality of the factors together, mitigating the effect of changing business conditions.

Given that there is strong cyclicality in factor returns, with certain factors underperforming for significant periods of time and outperforming in others, the question arises as to whether an investor can tactically move between the different factor portfolios in anticipation of changing economic conditions to get a higher return. This process of switching investments between different factors across time is called style or factor timing.

Academic and industry experts have debated the ability of investors to know when to switch between factor portfolios and the benefits of switching. A series of authors have claimed that they are able to predict factor movements ex ante and therefore are able to construct tactical portfolios that outperform a buy-and-hold strategy.[38] But other authors have examined the performance of mutual funds that switch between factors and found that their performance is worse than funds that maintain a consistent exposure to all of the factors.[39] Cliff Asness of AQR Capital Management found "timing strategies to be quite weak historically."[40] Rather than trying to time factors, he recommends that investors "instead focus on identifying factors that they believe in over the very long haul, and aggressively diversify across them."[41] Robert Arnott, the founder and chairman of Research Affiliates, and his co-authors take the alternative perspective that "active timing of smart beta strategies and/or factor tilts can benefit investors. We find that performance can easily be improved by *emphasizing* the factors or strategies that are trading cheap relative to their historical norms and by *deemphasizing* the more expensive factors or strategies."[42]

Data Analysis

In its decision process about introducing multifactor ETFs, iShares wanted to consider the value added of its potential US large-mid-cap multifactor ETF relative to the size, value, quality, and momentum factor ETFs it already sold, and how it compared to the traditional investing approach using asset classes (e.g. large-cap, mid-cap, international, etc.), which were market capitalization–based portfolios.

To put its analysis in perspective, iShares wanted to reexamine Fama and French's five-factor analysis and the momentum factor. The original Fama and French study used data from 1964–2012 but iShares wanted to know if those findings held over shorter periods of time. iShares was particularly interested in 2005–2014, which was the period for which it had data for its smart beta factor ETFs. The data for this analysis is in **Exhibit 1**.

To understand the benefits of factor investing relative to traditional asset class–based investing, iShares compared its potential US multifactor ETF relative to other ETFs it already sold. The monthly returns from 2005–2014 for different ETFs or their proxies are presented in **Exhibit 2**.* The Markowitz minimum-variance frontiers for different scenarios are presented in **Exhibits 3** and **4**.

Conclusion

Although there was substantial evidence that the returns for individual factor portfolios outperformed traditional market capitalization portfolios, there was no such evidence for multifactor portfolios, so their value added from an investment perspective was still an open question. Therefore, it was still uncertain whether there would be a need or a demand in the marketplace for multifactor ETFs. iShares was not only the market leader in the overall ETF market, but also the leader in the smart beta ETF market. To avoid tarnishing its brand name, iShares would not introduce multifactor ETFs unless their value was proven.

* The MSCI factor indexes' returns are used as proxies because the actual iShares ETFs are new to the marketplace and do not have a long time series of returns. When MSCI created its factor indexes it provided a history of the data, so the time series available to analyze is long enough to study.

Since iShares already sold smart beta ETFs that targeted individual factors, it had to compare the performance of the new multifactor ETFs to its existing smart beta ETFs, as well as to traditional market capitalization ETFs. The executives in the Factor Strategies Group still had some important analysis to conduct before they made their final decision about these new multifactor ETFs.

Exhibit 1: Historical Data for Fama and French's Financial Characteristics Decile Sorted Portfolios

See the Exhibits Excel file

Source: See the source notes to Figures 1–6 for sources, with the difference being that this is monthly data for the period 2005–2014 and the data used in those figures is annual data for 1964–2014.

Exhibit 2: Monthly Returns for Selected MSCI Indexes and iShares ETFs

See the Exhibits Excel file

Source: The data for the MSCI indexes is from http://www.MSCI.com, accessed August 2016, and the iShares data is from the Center for Research in Security Prices.

Exhibit 3: Minimum-Variance Frontiers Calculated from Different Combinations of the MSCI Factor Indexes and iShares ETFs

See the Exhibits Excel file

Source: Author's calculations using the data from Exhibit 2.

Exhibit 4: Minimum-Variance Frontiers Calculated from Different Combinations of the MSCI Factor Indexes and iShares Bond ETF

See the Exhibits Excel File

Source: Author's calculations using the data from Exhibit 2.

Endnotes

1 BlackRock website, accessed September 2016, http://www.blackrock.com.

2 iShares website, accessed September 2016, http://www.ishares.com, and the author's calculations using data from the Center for Research in Security Prices.

3 Fama and French's first circulated draft was in 2013; their final published paper is: E. F. Fama and K. R. French, "A Five-Factor Asset Pricing Model," *Journal of Financial Economics* 116 (2015): 1–22.

4 E. F. Fama and K. R. French, "The Cross-Section of Expected Stock Returns," *Journal of Finance* 47 (1992): 441–65.

5 E. F. Fama and K. R. French, "Multifactor Explanations of Asset Pricing Anomalies," *Journal of Finance* 51 (1996): 55–84.

6 See M. Bennan, T. Chordia, and A. Subrahmanyam, "Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns," *Journal of Finance* 49 (1998): 345–73.

7 See X. F. Zhang, "Information Uncertainty and Stock Returns," *Journal of Finance* 61 (2006): 105–37.

8 See, for example, S. Basu, "The Relationship Between Earnings Yield, Market Value, and Returns for NYSE Common Stocks: Further Evidence," *Journal of Financial Economics* 12 (1983): 129–56.

9 R. Novy-Marx, "The Other Side of Value: The Gross Profitability Premium," *Journal of Financial Economics* 108 (2013): 1–2.

10 Ibid., 1.

11 For background, see S. Titman, K. Wei, and F. Xie, "Capital Investments and Stock Returns," *Journal of Financial and Quantitative Analysis* 39 (2004): 677–700. Also see G. Aharoni, B. Grundy, and Q. Zeng, "Stock Returns and the Miller Modigliani Valuation Formula: Revisiting the Fama French Analysis," *Journal of Financial Economics* 110 (2013): 347–57.

12 For background of momentum, see N. Jegadeesh and S. Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* 48 (1993): 65–91, and M. M. Carhart, "On Persistence in Mutual Fund Performance," *Journal of Finance* 52 (1997): 57–82. Also see C. S. Asness, "Variables That Explain Stock Returns," PhD dissertation, University of Chicago, Graduate School of Business (1994).

13 E. F. Fama and K. R. French, "Dissecting Anomalies with a Five-Factor Model," *Review of Financial Studies* 29 (2016): 1–35.

14 See, for example, C. S. Asness et al., "Fact, Fiction, and Value Investing," *Journal of Portfolio Management* 42 (2015): 34–52.

15 C. S. Asness, T. J. Maskowitz, and L. H. Pedersen, "Value and Momentum Everywhere," *Journal of Finance* 48 (2013): 929–85.

16 D. K. Hirshleifer and A. Subrahmanyam, "Investor Psychology and Security Market Under- and Over-Reactions," *Journal of Finance* 53 (1998): 1839–85.

17 For details on what ETFs are, see J. Hill, D. Nadig, and M. Hougan, "A Comprehensive Guide to Exchange-Traded Funds (ETFs)," CFA Research Foundation, May 2015.

18 C. S. Asness et al., "Fact, Fiction, and Value Investing," *Journal of Portfolio Management* 42 (2015): 34–52.

19 See, for example, R. Arnott et al., "How Can 'Smart Beta' Go Horribly Wrong?" Research Affiliates, February 2016, and R. Arnott, N. Beck, and V. Kalesnik, "Timing 'Smart Beta' Strategies? Of Course! Buy Low, Sell High!" Research Affiliates, September 2016.

20 See C. S. Asness, "How Can a Strategy Still Work If Everyone Knows About It?" AQR, 2015.

21 See, for example, R. Ball, "Anomalies in Relationsips Between Securities' Yields and Yield Surrogates," *Journal of Financial Economics* 6 (1978): 103–26.

22 See, for example, R. A. Haugen and N. L. Baker, "Commonality in the Determinants of Expected Stock Returns," *Journal of Financial Economics* 41 (1996): 401–39. More recently an alternative perspective of the volatility effect as a CAPM beta effect has been studied; see A. Frazzini and L. Pedersen, "Betting Against Beta," *Journal of Financial Economics* 111 (2014): 1–25.

23 H. Bell, "Daily ETF Watch: SSgA's US Quality Mix SPDR," December 22, 2014, http://www.etf.com/sections/daily-etf-watch/24115-daily-etf-watch-ssgas-us-quality-mix-spdr.html, and JPMorgan Diversified Return Global Equity ETF, accessed September 2016, https://am.jpmorgan.com/us/en/asset-management/gim/adv/products/d/jpmorgan-diversified-return-global-equity-etf-etf-shares-46641q100.

24 BlackRock, "Smart Beta Guide," pg. 12, accessed August 2016, https://www.blackrock.com/au/intermediaries/literature/whitepaper/ blackrock-smart-beta-guide-en-au.pdf.

25 R. D. Arnott, J. C. Hsu, and P. Moore, "Fundamental Indexation," *Financial Analysts Journal* 61 (2005): 83–99.

26 Research Affiliates website, accessed September 2016, http://www.researchaffiliates.com.

27 MSCI, "MSCI Risk Weighted Indexes Methodology," June 2014.

28 MSCI, "MSCI Enhanced Value Indexes Methodology," May 2015.

29 MSCI, "MSCI Quality Indexes Methodology," August 2014.

30 MSCI, "MSCI Momentum Indexes Methodology," September 2014.

31 See, for example, "MSCI Enhanced Value Indexes Methodology."

32 MSCI website, accessed September 2016, http://www.msci.com.

33 L. Woodall, "Index Providers Clash Over Evolution of Multi-Factor Products," October 2, 2015, http://www.risk.net/structured-products/feature/2427846/index-providers-clash-over-evolution-of-multi-factor-products.

34 BlackRock, "Factor Investing: Unlocking the Real Drivers of Returns," accessed August 2016, https://www.blackrock.com/es/ literature/brochure/factor-investing-unlocking-drivers-of-return-en-lai.pdf.

35 See A. Ang, W. N. Goeztman, and S. Schaefer, "Evaluation of Active Management of the Norwegian Government Pension Fund—Global, Report to the Norwegian Ministry of Finance," December 14, 2009.

36 iShares, "Factor These Funds into Your Game Plan," accessed August 2016, https://www.ishares.com/us/literature/product-brief/ishares-msci-factor-etfs-product-brief.pdf, and Q. J. Zhang et al., "The Link Between Macro-Economic Factors and Style Returns," *Journal of Asset Management* 10 (2009): 338–55.

37 J. Stoneberg and B. Smith, "Getting Smart about Beta," Invesco PowerShares white paper, accessed August 2016, https://www.invesco.com/static/us/financial-professional/contentdetail?contentId=634ff6163339f410VgnVCM100000c2f1bf0aRCRD.

38 See, for example, K. L. Miller et al., "Size Rotation in the U.S. Equity Market," *Journal of Portfolio Management* 39 (2013): 116–27.

39 A. J. Corbett, "Are Style Rotating Funds Successful at Style Timing? Evidence from the US Equity Mutual Fund Market," working paper, February 2, 2016, https://ssrn.com/abstract=2736672.

40 C. S. Asness, "Resisting the Siren Song of Factor Timing," AQR, April 15, 2016.

41 Ibid.

42 Arnott, Beck, and Kalesnik, "Timing 'Smart Beta' Strategies? Of Course!"