May 2017

Why Factor Tilts Are Not Smart "Smart Beta"

Part II of Alice in Factorland

Rob Arnott, Mark Clements, PhD, and Vitali Kalesnik, PhD

This article is the second in a series we are publishing in 2017. The first article of the series showed that the factor returns realized by mutual fund managers can be very different from the returns investors might expect based on the funds' factor loadings. We find that the performance of the market, value, and momentum factors in live portfolios is sharply lower than their performance in theoretical model portfolios. If the results of long–short factor paper portfolios used in regression analysis to judge manager skill are not replicable with live assets, bad decisions may be made. This may be contributing to many of the new live factor strategies faring as poorly as they are, even though the periods over which their performance is being measured are too short to draw any meaningful conclusions.

Key Points

1. *Not all features of smart beta strategies that add value for investors can be replicated with simple factor tilts.*
2. *Whereas factor-replicated portfolios can match the short-run returns of smart beta strategies, they have higher turnover, much larger trading costs, smaller capacity, more frequent and prolonged benchmark underperformance, larger drawdowns, higher residual risk, and lower long-run returns.*
3. *Implementation matters! Really* smart *smart beta strategies should be designed to optimally capture factor return premiums and be able to deliver them to investors after trading costs.*

FURTHER READING

April 2017
The Incredible Shrinking Factor Return
Rob Arnott, Vitali Kalesnik, PhD, and Lillian Wu

February 2017
Forecasting Factor and Smart Beta Returns
Rob Arnott, Noah Beck, Vitali Kalesnik, PhD, and Lillian Wu

January 2017
How Not to Get Fired with Smart Beta Investing
John West, CFA, Vitali Kalesnik, PhD, and Mark Clements, PhD

CONTACT US

Web: www.researchaffiliates.com

Americas
Phone: +1.949.325.8700
Email: info@researchaffiliates.com
Media: hewesteam@hewescomm.com

EMEA
Phone: +44.2036.401.770
Email: uk@researchaffiliates.com
Media: ra@jpespartners.com

In this article, we challenge the common view that smart beta strategies and factor tilts are equivalent. Initially, the term "smart beta" referred to strategies that broke the link between the price of a stock and its weight in the portfolio or index. Capitalization weighting does not do that—neither does a portfolio that applies factor tilts to a cap-weighted starting portfolio.

Some have suggested that certain smart beta strategies are essentially factor tilt strategies in disguise, which can be replicated with factor tilts applied to a cap-weighted market portfolio. We test this assertion by replicating three first-generation smart beta strategies—Fundamental Index™, equal weight, and minimum variance—with factor tilts. Creating factor-replicated portfolios that match the factor loadings of these smart beta strategies is easy, but the factor-replicated portfolios are poor substitutes for their smart beta counterparts: performance is poor, turnover is high, and capacity is terrible. Why? The simple answer is that construction details matter in achieving both lower trading costs and higher performance.

In the third article of the series, we will examine whether expected factor returns based on relative valuation can forecast mutual fund performance better than existing models, whose typical inputs are fees, turnover, and past returns. The fourth paper in our series will take a deep dive into momentum to explore why live results for momentum strategies are so starkly inferior to the results of theoretical model portfolios and to ask how momentum can be preserved as a value-added strategy.

A walk along Canal Street in New York City on a typical day winds around numerous vendors selling replica Rolexes at bargain prices. The replicas' quality varies from vendor to vendor, but for the most part they all look very much like the real deal and might even keep time reasonably well. But a buyer of a replica Rolex accepts certain risks avoided when buying an original: the watch is not guaranteed, may break easily, and may even contain toxic chemicals used to simulate gold that can turn skin green. To state the obvious: all Rolexes are watches, but not all watches are Rolexes.

We assert the same logic holds for smart beta investment strategies. All smart beta strategies have factor tilts (useful in that factors can educate investors about strategy tendencies and return drivers), and factor tilt strategies can reasonably replicate the *short-term* performance of smart beta strategies. We show, however, that simple factor tilts based on the factor construction popularized in the academic literature are a poor way to capture the long-term performance of smart beta strategies. Smart beta strategies—as originally defined by Towers Watson—generally deliver superior performance, both before and after trading costs, and have more favorable portfolio characteristics, such as turnover, trading costs, and capacity. Although all smart beta strategies have factor tilts, not all factor tilts are smart beta strategies.

> ***"Simple factor tilts...are a poor way to capture the long-term performance of smart beta strategies."***

Smart Beta Return Performance

Towers Watson coined the term "smart beta" around 2009, inspired by the Fundamental Index and other strategies, to encompass an array of strategies that break the link between the price of a stock and its weight in the portfolio. Towers Watson found many examples, including among them equal weight, Fundamental Index, minimum variance, low volatility, EDHEC's Risk-Efficient strategy, and TOBAM's Maximum Diversification strategy. A unifying attribute of these strategies is that they exploit a simple fact: market capitalization–weighted strategies weight every stock that is currently overvalued (hence, destined to underperform in the future) in the portfolio above its fair-value weight, and underweight every undervalued stock.

Advocates of cap-weighted indexing correctly observe we cannot know which stock is overvalued and which is undervalued because we cannot know fair value, and accordingly we cannot know fair-value weight. They argue this seeming Achilles' heel of capitalization weighting does not present a problem. But if we can break the link between the price of a stock and its portfolio weight, we will no longer assuredly overweight overvalued stocks and underweight undervalued stocks. An over- or undervalued stock is roughly equally as likely to be above as below its fair-value weight, *so the errors cancel!* This has been referred to as rebalancing alpha and is a shared attribute of all generation-one smart beta strategies.

Ample evidence exists that these early smart beta approaches add value. We compare three: Fundamental Index, which weights the top 1,000 US stocks by the fundamental economic footprint of the 1,000 largest businesses in the macroeconomy; equal weight, which equally weights the top 1,000 US stocks (selected by market capitalization); and minimum variance, which optimizes (using the top 1,000 US stocks by market cap, subject to constraints) to create the lowest-possible-risk portfolio.[1] A comparison of the performance characteristics and factor model return attributions of these strategies is provided in **Table 1**. Before trading costs, all three add 130–200 basis points (bps) of total return a year above the market capitalization–weighted top 1,000 stocks, and all three have sizable Sharpe ratios and information ratios over the past half-century.

Pundits have argued that the Fundamental Index is nothing more than a value strategy, but in live experience the Fundamental Index outperformed value over a period (2006 through February 2017) when value was savaged: on an

Table 1. Return Performance and Factor Loadings for Fundamental Index, Equal-Weight, and Minimum-Variance Strategies, Jan 1974–Jun 2016

Panel A. Risk and Return Characteristics, Annualized

				Relative to Benchmark		
Investment Allocation	Return	Volatility	Sharpe Ratio	Value-Add	Tracking Error	Information Ratio
Fundamental Index	12.9%	15.3%	0.53	1.8%	4.3%	0.42
Equal Weight	13.1%	16.9%	0.49	2.0%	4.8%	0.41
Minimum Variance	12.4%	13.3%	0.57	1.3%	5.7%	0.23
Cap Weight US 1000	11.1%	15.4%	0.41			

Panel B: Fama–French Three-Factor Model Plus Momentum

	Alpha (Ann.)	Market	Value	Size	Momentum	R^2
Fundamental Index	0.97%***	0.98***	0.35***	-0.08***	-0.07***	97.9%
	(2.74)	(147.47)	(33.46)	(-8.07)	(-10.23)	
Equal Weight	0.67%	1.03***	0.18***	0.24***	-0.02***	97.2%
	(1.48)	(120.96)	(13.78)	(19.59)	(-2.73)	
Minimum Variance	1.59%**	0.83***	0.16***	-0.16***	0.05***	87.4%
	(2.10)	(58.05)	(6.97)	(-7.61)	(3.10)	

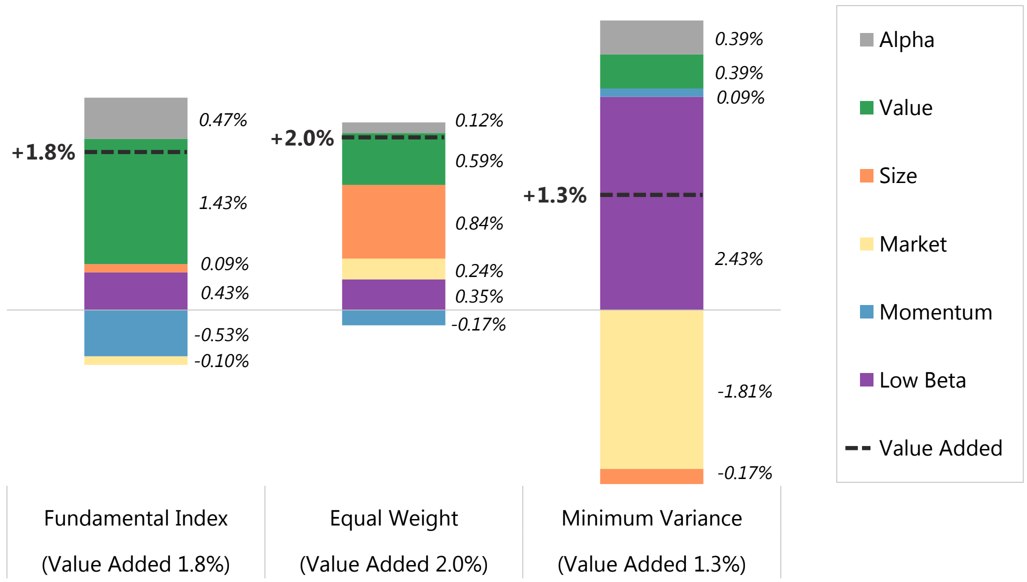
Panel C: Fama–French Three-Factor Model Plus Momentum and BAB Factor

	Alpha (Ann.)	Market	Value	Size	Momentum	BAB	R^2
Fundamental Index	0.67%*	0.98***	0.33***	-0.08***	-0.08***	0.04***	98.1%
	(1.90)	(150.06)	(29.20)	(-8.31)	(-11.47)	(4.83)	
Equal Weight	0.38%	1.02***	0.16***	0.24***	-0.04***	0.04***	97.3%
	(0.83)	(121.87)	(11.25)	(19.77)	(-3.80)	(3.57)	
Minimum Variance	0.51%	0.82***	0.08***	-0.16***	0.00	0.16***	88.9%
	(0.71)	(61.28)	(3.31)	(-8.24)	(0.26)	(8.45)	

Note: *** Significance at the 1% level, **Significance at the 5% level, * Significance at the 10% level. The BAB factor is the betting-against-beta factor of Frazzini and Pedersen (2014).

Source: Research Affiliates, LLC, based on data from CRSP and Compustat.

Figure 1. Factor Attribution of Smart Beta Value-Add over Cap-Weighted Benchmark, Jan 1974–Jun 2016



Source: Research Affiliates, LLC, based on data from CRSP and Compustat.

annualized basis, the Fundamental Index delivered 9.29%, better than the 7.42% of the Russell 1000 Value Index, the 8.16% earned by the S&P 500 Index, and even the 8.99% earned by the Russell 1000 Growth Index.[2] In other words, the Fundamental Index beat Russell Growth in a decade when growth beat value! So much for the early cynics.

Similarly, the equal-weight strategy is said to be a predominantly small-cap value strategy, and minimum variance a predominantly small-cap, low-beta, and value strategy. These three unique strategies, each with a value bias, won across three broad geographies (the US, international, and emerging markets) in a period when value lost (Jan 2006–Feb 2017)—again, so much for the critics.

Today the definition of smart beta has become quite broad. Smart beta now seems to encompass any quant-like strategy that claims some degree of transparency. To our astonishment, some surveys even list Russell 1000 Growth and Value as smart beta; both are cap-weighted, and when combined they equal the market! Many extend the term to include factor tilt and multi-factor strategies, even though most of these strategies begin with and anchor on cap-weighting.

Factor attribution helps investors better understand the systematic bets at work in their portfolios as well as the drivers of return. But can these, or any, strategies be fully reduced to their factor exposures? In other words, net of their factor exposures, is it true that smart beta strategies provide no further benefits to investors? For example, some have suggested that the Fundamental Index is nothing more than a pure value strategy.[3] In a narrow sense the Fundamental Index is *absolutely* value in that it weights each stock in proportion to its capitalization weight times its valuation ratio.[4] We will show, however, that this specific form of value investing captures the value premium and benefits investors in ways that a simple factor tilt strategy cannot.

The Fundamental Index strategy's factor exposures suggest a modest and statistically significant alpha (especially in international applications, as in Arnott et al. [2013]), with a large value exposure and a persistent anti-momentum exposure, whether we use a four-factor model (Fama–French plus momentum) or a five-factor model, which also includes the Frazzini–Pedersen (2014) betting-against-beta (BAB) factor. Furthermore, as **Figure 1** shows, the factor exposures account for about 74% of the value-add of the Fundamental Index in excess of the cap-weighted benchmark, leaving 26% of the value-add unexplained by the full collection of factor exposures.

> *"Trading costs are much higher for the replicated portfolios."*

In part, the alpha of the Fundamental Index comes from the fact that the Fama–French value factor is itself not pure value, because it cap-weights the value and growth portfolios. More important, however, the Fundamental Index is value "done better" because it regularly rebalances against the market's constantly changing perceptions of value. As we have explained in the past, Fundamental Index alpha comes both from buying stocks that are relatively cheap (the value effect) and by dynamically taking a deeper value loading whenever those value stocks are unusually cheap. So, the Fundamental Index *is*—viewed from its weighting metric—a pure value strategy, but it is also a better means of capturing the value premium than simply tilting away from market cap using a static tilt with the theoretical value factor. Although the Fundamental Index strategy creates a value tilt (and an anti-momentum tilt and a variable, but minor, small-cap tilt), the process cannot be reverse engineered. The bottom line is that in recreating the factor tilts of smart beta strategies much is lost in translation.

Smart Beta Factor–Replicated Portfolios

Can we replicate these smart beta strategies using factor tilts? Of course we can—approximately. We employ a five-factor model consisting of the standard Fama–French three-factor model, which includes the market, value, and size factors augmented by the momentum factor and the Frazzini–Pedersen low beta, or BAB, factor. Using the factor exposures of the smart beta strategies from this model, along with factor portfolio weights, we construct portfolios that tilt away from market cap (our specific methodology is detailed in the appendix). These factor-replicated portfolios have nearly identical factor loadings, on average over time, to the smart beta strategies.

Because factors are built from long–short factor portfolios, we can reverse engineer the three smart beta strategies we analyze by starting with the cap-weighted market and adding in the long–short portfolios with weights that match the factor loadings of the smart beta strategies. In order to avoid look-ahead bias, we estimate factor loadings using expanding window regressions. We use the first 10 years of data to estimate factor loadings in constructing the weights for the subsequent month, and the first 10 years plus one month of data to estimate loadings to construct the subsequent month's weights, and so on.[5]

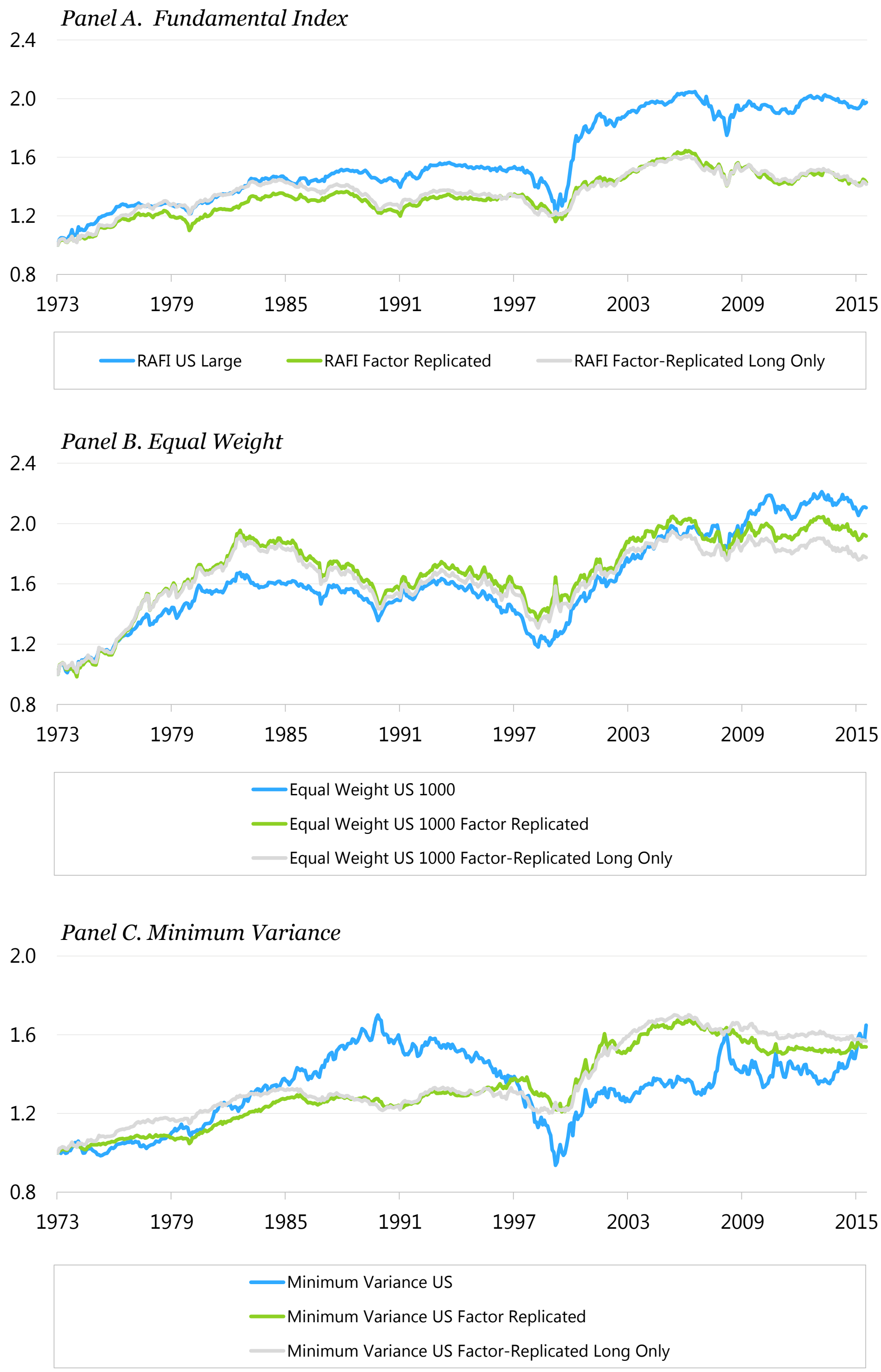
Factors are generally long–short portfolios. Because smart beta strategies are generally long-only portfolios, we create an alternative long-only factor-replicated strategy. This long-only strategy excludes the short weights in the long–short factor-replicated strategy, then renormalizes the weights (including cash) to sum to 100%. The result is that we have two versions of the replicated portfolio: one is a full replication, using long–short portfolios, and the other is a more practical long-only replication strategy.

The time series of excess returns for each of the three strategies and their respective replicated portfolios over our sample period are plotted in **Figure 2, Panels A–C**. Clearly, the value added by the replicating strategies tracks the ups and downs of the original generation-one smart beta strategies reasonably well, but not at all precisely. We do not show the returns here, but the replicating strategies deliver rolling five-year excess returns relative to the cap-weighted market with an average correlation of 79% when compared with the original smart beta strategies we are seeking to match. Game over for the debate on smart beta versus factors? Hardly!

Can Smart Beta Returns Be Replicated with Factor Tilts?

The factor-replicated portfolios do a reasonable job of reproducing the average annualized returns and risk characteristics of the smart beta strategies over our sample period.

Figure 2. Cumulative Value-Add Relative to Cap-Weighted Market Benchmark of Smart Beta Strategies and Factor-Replicated Portfolios, Jan 1973–Jun 2016



Source: Research Affiliates, LLC, based on data from CRSP and Compustat.

This should not be surprising *because they are constructed to do so*. Nevertheless, the Fundamental Index, equal-weight, and minimum-variance portfolios generate 86, 25, and 18 more basis points of value-add a year, respectively, than their factor-replicated strategies, and with the exception of minimum variance, have higher Sharpe ratios and information ratios; minimum variance has roughly the same Sharpe ratio and lower information ratio. *These data are all before trading costs*.

The factor exposures of the replicated portfolios, reported in **Table 2**, have the same signs and relative magnitudes and factor attributions to excess returns as the smart beta strategies (once again, by construction).[6]

The story for minimum variance is slightly different. The market exposure of this replicated portfolio (0.88) is larger than the smart beta strategy (0.82), presenting a mild setback if the objective of the strategy is a lower beta and a lower volatility. The setback becomes obvious and more alarming if we strip out the short positions—to more closely mimic a long-only smart beta strategy—and look at the volatility and market factor loading for this long-only factor-replicated strategy. The long-only factor replication no longer looks like a minimum-variance strategy: it now sports a market beta of 0.91 with volatility rivaling that of the market (14.4%). An investor who wants to replicate minimum variance with factors would be hugely disappointed!

Although the factor-replicated portfolios deliver reasonable value-add, Sharpe ratios, and information ratios, the average return statistics mask just how different the replicated portfolio and smart beta strategy returns are. If we look more closely at the tracking errors, reported in **Table 3**, of the replicated portfolios to the smart beta strategies *they seek to replicate*, we find striking dissimilarities. Indeed, it seems the replicating portfolios are often roughly as different from the smart beta strategies—which they are seeking to replicate—as they are from the market!

Portfolio Characteristics

Simply looking at portfolio returns obscures other important ways that smart beta strategies and their factor-replicated portfolios are quite different. For instance, the Fundamental Index and its factor-replicated portfolios trade at a discount relative to the market, as is the nature of a Fundamental Index strategy.[7] If we reweight the popular (and expensive) growth stocks *down* to their economic scale using fundamental measures of a company's percentage weight in the macroeconomy (by sales, profits, book value, and dividends) and reweight the unloved (and cheap) value stocks *up* to their economic scale, we are introducing a value tilt.

A comparison of valuation ratios, presented in **Table 4**, shows that the Fundamental Index trades slightly cheaper than its replicated portfolios. The replicated portfolios have a lower price-to-book ratio (due to the deep tilt toward the single value factor, which uses book-to-price as its only signal for value), while the Fundamental Index tends to select stocks with higher dividends. Equal weight and its replicated portfolios trade at a slight discount to the market with noticeable differences across valuation ratios, particularly in dividend yield. The differences across valuation ratios is the most striking in the case of minimum variance. The factor-replicated portfolios' significant value and low-beta tilts result in a much larger market discount and tend to assign large weights to stocks whose valuations are depressed.

Comparing each portfolio's periods of outperformance and underperformance relative to the cap-weighted benchmark, as reported in **Table 5**, reveals further differences. We find the factor-replicated portfolios underperform the benchmark twice as often (on a rolling five-year basis) as the Fundamental Index, with an average duration of underperformance more than twice as long, and a *maximum* duration of underperformance up to two years longer than the Fundamental Index. The equal-weight factor-replicated portfolios also underperform the benchmark more often, but with average and maximum durations similar to the equal-weight portfolio. In terms of drawdown, Fundamental Index and equal weight have nearly identical maximum drawdowns to their factor-replicated portfolios.

The minimum-variance factor-replicated portfolios underperform the benchmark about as frequently as the smart

Table 2. Return Performance, Jan 1974–Jun 2016

Panel A. Risk and Return Characteristics, Annualized

				Relative to Cap US 1000		
Investment Allocation	Return	Volatility	Sharpe Ratio	Value-Add	Tracking Error	Information Ratio
Fundamental Index	12.9%	15.3%	0.53	1.8%	4.3%	0.42
Factor Replicated	12.0%	15.2%	0.47	0.9%	3.4%	0.28
Factor-Replicated Long Only	12.0%	15.7%	0.46	0.9%	3.2%	0.29
Equal Weight	13.1%	16.9%	0.49	2.0%	4.8%	0.41
Factor Replicated	12.8%	17.4%	0.46	1.7%	5.3%	0.32
Factor-Replicated Long Only	12.6%	16.8%	0.46	1.5%	5.1%	0.30
Minimum Variance	12.4%	13.3%	0.57	1.3%	5.7%	0.23
Factor Replicated	12.2%	13.7%	0.54	1.1%	3.0%	0.38
Factor-Replicated Long Only	12.3%	14.4%	0.52	1.2%	2.6%	0.46
Cap Weight US 1000	11.1%	15.4%	0.41			

Panel B: Fama–French Three-Factor Model Plus Momentum and BAB Factor

	Alpha (Ann.)	Market	Value	Size	Momentum	BAB	R^2
Fundamental Index	0.67%* (1.90)	0.98*** (150.06)	0.33*** (29.20)	-0.08*** (-8.31)	-0.08*** (-11.47)	0.04*** (4.83)	98.0%
Factor Replicated	-0.03% (-0.32)	0.98*** (596.60)	0.30*** (105.39)	-0.03*** (-14.22)	-0.07*** (-36.25)	0.03*** (11.03)	99.9%
Factor-Replicated Long Only	-0.03% (-0.39)	0.99*** (622.38)	0.24*** (87.96)	0.10*** (42.68)	-0.05*** (-28.42)	0.01*** (3.38)	99.9%
Equal Weight	0.38% (0.83)	1.02*** (121.87)	0.16*** (11.25)	0.24*** (19.77)	-0.04*** (-3.80)	0.04*** (3.57)	97.3%
Factor Replicated	0.08% (0.56)	1.04*** (398.76)	0.18*** (39.45)	0.37*** (97.19)	-0.01*** (-3.06)	0.00 (0.31)	99.8%
Factor-Replicated Long Only	0.04% (0.29)	1.00*** (363.71)	0.16*** (34.56)	0.36*** (89.69)	-0.01* (-1.83)	0.01** (2.06)	99.7%
Minimum Variance	0.51% (0.71)	0.82*** (61.28)	0.08*** (3.31)	-0.16*** (-8.24)	0.00 (0.26)	0.16*** (8.45)	88.9%
Factor Replicated	-0.09% (-0.72)	0.88*** (374.21)	0.06*** (15.46)	-0.11*** (-31.58)	-0.01*** (-4.98)	0.17*** (49.97)	99.7%
Factor-Replicated Long Only	0.28%** (1.96)	0.91*** (346.55)	0.07*** (15.20)	0.05*** (12.98)	-0.03*** (-11.56)	0.10*** (27.89)	99.6%

Note: *** Significance at the 1% level, **Significance at the 5% level, * Significance at the 10% level. The BAB factor is the betting-against-beta factor of Frazzini and Pedersen (2014).

Source: Research Affiliates, LLC, based on data from CRSP and Compustat.

Table 3. Tracking Error, Value-Add, and Information Ratio for Smart Beta Strategies Relative to Factor-Replicated Portfolios, Jan 1974–Jun 2016

	Factor Replication			Relative to Cap US 1000		
Investment Allocation	Value-Add	Tracking Error	Information Ratio	Value-Add	Tracking Error	Information Ratio
Fundamental Index	0.86%	2.3%	0.38	0.88%	3.3%	0.27
Equal Weight	0.25%	3.2%	0.08	0.45%	3.1%	0.15
Minimum Variance	0.18%	4.6%	0.04	0.13%	5.5%	0.02

Source: Research Affiliates, LLC, using data from CRSP and Compustat.

Table 4. Portfolio Discounts to the Market and Valuation Ratios, as of June 2016

	Cap US 1000	Fundamental Index	Factor Replication	Factor-Replication Long Only
Discount to Market	—	0.70	0.72	0.78
Price to Five-Yr. Avg. Earnings	22.24	17.73	17.08	19.07
Price to Book	2.80	1.89	1.51	1.70
Price to Sales	1.67	0.99	1.25	1.25
Dividend Yield	1.92%	2.53%	2.17%	1.97%
	Cap US 1000	**Equal Weight**	**Factor Replication**	**Factor-Replication Long Only**
Discount to Market	—	0.98	0.81	0.86
Price to Five-Yr. Avg. Earnings	22.24	26.18	20.55	21.84
Price to Book	2.80	2.55	1.85	1.95
Price to Sales	1.67	1.35	1.17	1.23
Dividend Yield	1.92%	1.78%	4.87%	4.58%
	Cap US 1000	**Minimum Variance**	**Factor Replication**	**Factor-Replication Long Only**
Discount to Market	—	1.21	0.95	0.91
Price to Five-Yr. Avg. Earnings	22.24	26.08	21.22	22.15
Price to Book	2.80	4.32	2.22	2.14
Price to Sales	1.67	1.86	1.86	1.44
Dividend Yield	1.92%	1.79%	4.71%	4.51%

Source: Research Affiliates, LLC, using data from CRSP and Compustat.

beta strategy, and have shorter average and maximum durations. The minimum-variance strategy has a much smaller maximum drawdown and shorter longest drawdown than its replicated portfolios; this is precisely what a minimum-variance strategy is designed to deliver. The replication strategies have a maximum drawdown of 50%, very near that of the market, forfeiting the raison d'être of minimum variance.

Certainly, an investor cares about a strategy's return, valuation ratio, and performance relative to a benchmark, but trading costs and capacity, displayed in **Table 6**, are also very important. Here, a stark difference appears between the smart beta strategies and their replicated portfolios. The Fundamental Index factor-replicated portfolios are around 20–30 times more expensive to trade (assuming an AUM of $10 billion) than the Fundamental Index.[8] Furthermore, annualized returns net of trading costs for the Fundamental Index factor-replicated portfolios are lower by 107–117 bps, and would only get worse with larger AUM. We see a similar pattern for the equal-weight and minimum-variance factor-replicated portfolios.[9]

Trading costs are much higher for the replicated portfolios because they inherit a monthly rebalancing frequency from the momentum factor portfolio, whereas the Fundamental Index and equal-weight strategies are rebalanced annually and the minimum-variance strategy semi-annually. This difference becomes apparent when comparing portfolio turnover. The Fundamental Index factor-replicated portfolios have five-times higher turnover than the turnover of the Fundamental Index, while equal-weight and minimum-variance factor-replicated portfolios turn over about two to three times as much as the smart beta strategies they replicate.

When these portfolios are traded in a live setting their capacity is a very important consideration. We measure capacity as the amount of AUM that would generate an estimated 50 bps of price impact in the trading level of the portfolio.[10] Again, a large difference emerges between the smart beta strategies and their factor-replicated portfolios when comparing their relative capacities. The Fundamental Index has around 25–40 times larger capacity than its factor-replicated portfolios. The replicated portfolios not only have far higher turnover, they also have many more large positions in illiquid stocks—a triumph of quant paper portfolios over practical realities. Meanwhile, equal weight has 5–6 times larger capacity, and minimum variance almost twice the capacity of its replicated portfolios. The differences between the trading costs, turnover, and capacity of these smart beta strategies versus their factor tilt–replicated portfolios are substantial and directly impact the efficacy of any factor tilt that seeks to replicate a particular smart beta strategy.

A Deeper Dive into Portfolio Holdings

Factor exposures are just one source of risk in evaluating smart beta strategies and their factor-tilt replicated portfolios. The replicated portfolios ought to look vaguely like the portfolios they ostensibly seek to replicate. The top 10 holdings of these smart beta strategies and their replicated portfolios at the most recent rebalancing show some overlap for Fundamental Index, but the differences for the other two are astonishing.[11]

Let's first look at the Fundamental Index. The Fundamental Index gives almost twice as much weight to Exxon as its replicated portfolio, and only half as much weight to Berkshire Hathaway; meanwhile, Walmart, which is the second-largest US business in the Fundamental Index, doesn't even crack the top 10 in the replicated portfolio. The core principle of the Fundamental Index is to use the size of a business—blending sales, profits, book value, and dividends as a measure of a company's economic footprint in the macroeconomy—as a stable, economically meaningful anchor to contra-trade against the market's constantly changing expectations and speculations. Even though 7 of the top 10 stocks on both lists are the same, the replicating portfolios are not conforming to a guiding principle of the Fundamental Index.

For equal weight, the results are really quite shocking. The replicating portfolios are not even vaguely equally weighted. Furthermore, the names at the top of the list

Table 5. Portfolio Performance Based on Five-Year Rolling Monthly Returns in Excess of the Cap-Weighted US Top 1,000 Stocks, Jan 1979–Jun 2016

	Fundamental Index	Factor Replication	Factor-Replication Long Only
Frequency of Underperformance	18%	36%	39%
Average Duration of Shortfall (Years)	0.79	1.66	1.88
Longest Duration of Shortfall (Years)	2.58	4.83	5.67
Maximum Drawdown	-56%	-56%	-55%
Longest Drawdown (Years)	4.75	5.58	5.50
	Equal Weight	**Factor Replication**	**Factor-Replication Long Only**
Frequency of Underperformance	29%	35%	40%
Average Duration of Shortfall (Years)	2.31	1.77	2.09
Longest Duration of Shortfall (Years)	5.33	5.25	6.42
Maximum Drawdown	-52%	-55%	-53%
Longest Drawdown (Years)	3.58	4.75	3.83
	Minimum Variance	**Factor Replication**	**Factor-Replication Long Only**
Frequency of Underperformance	38%	31%	39%
Average Duration of Shortfall (Years)	3.86	2.36	2.51
Longest Duration of Shortfall (Years)	10.17	6.42	6.67
Maximum Drawdown	-38%	-50%	-51%
Longest Drawdown (Years)	3.83	4.83	4.33

Source: Research Affiliates, LLC, using data from CRSP and Compustat.

Table 6. Portfolio Trading Costs, Capacity, Turnover, and Leverage, Jan 1974–Jun 2016

	Annual Return	Ann. Return Net of Costs	Long Leg Turnover	Short Leg Turnover	Trading Cost (bps)	Capacity ($Bn)	Avg. Long Leverage	Avg. Short Leverage
Fundamental Index	12.9%	12.9%	11%		1	615	100%	0%
Factor Replicated	12.0%	11.7%	57%	15%	32	16	113%	13%
Factor-Replicated Long Only	12.0%	11.8%	50%		20	25	100%	0%
Equal Weight	13.1%	13.0%	18%		4	116	100%	0%
Factor Replicated	12.8%	12.6%	36%	2%	23	19	104%	1%
Factor-Replicated Long Only	12.6%	12.4%	65%		20	25	100%	0%
Minimum Variance	12.4%	12.2%	25%		19	26	100%	0%
Factor Replicated	12.2%	11.9%	37%	14%	35	14	111%	11%
Factor-Replicated Long Only	12.3%	12.1%	75%		23	22	100%	0%

Source: Research Affiliates, LLC, using data from CRSP and Compustat.

are generally jumbo-cap stocks. How can a portfolio that purports to replicate a strategy that equally weights 1,000 stocks have nearly 12% invested in its top 10 holdings, which are all jumbo caps? This is, of course, a natural consequence of starting with a cap-weight portfolio and then applying factor tilts to match the factor loadings of the equal-weight portfolio.

Finally, the top 10 holdings of the minimum-variance strategy are entirely different from its replicated portfolio. In **Table 7**, not a single stock in the top 10 holdings of the replicating portfolio matches the minimum-variance strategy it seeks to replicate. Not one.

Conclusion

Today, smart beta strategies are attracting attention because they seek to capture systematic drivers of return in transparent, low-cost vehicles. We find that simple factor tilt strategies based on theoretical factors (although very helpful in educating investors on the systematic drivers of return) are rarely the best way to capture return premiums, particularly when taking into account transactions costs. Really *smart* smart beta strategies should be designed to optimally capture these return premiums and be able to deliver them to investors after trading costs. Factor tilts can be smart or stupid, expensive or cheap, but most of them are not smart beta based on the original definition that inspired Towers Watson to coin the expression.

"The Fundamental Index has around 25–40 times larger capacity than its factor-replicated portfolios."

We have also demonstrated that first-generation smart beta strategies cannot be replicated from their factor tilts. The strategy and its factor tilts are not one and the same. Whereas the factor loadings can easily be matched, the resulting factor-replicated portfolios typically have higher turnover, larger trading costs, smaller capacity, more frequent and prolonged benchmark underperformance, larger drawdowns, higher residual risk, and lower returns. Not a good result. Furthermore, as in the case of minimum variance or equal weight, a factor tilt portfolio may give us something very different from our intended portfolio. Not minimum variance. *Not* equal weight. *Not* even close!

Have we proven that factor tilts are not part of the family of smart beta strategies? Of course not. That's a matter of mere semantics. Just as Bill Sharpe rejects the term "smart beta," early advocates of smart beta may prefer the industry hew to a narrow definition of the term. A narrow definition limits the term to strategies that do not tie the portfolio weight to the share price, and using that narrow definition, factor tilts generally aren't smart beta. But, we don't control the definition.

Reciprocally, a broad definition allows just about any strategy to qualify, including factor tilts. Indeed, as many in the investment industry now define the term, almost any approach other than a full market cap–weighted index seems to qualify for the smart beta label, including cap-weighted market segments (e.g., Russell 1000 Value… or Growth), tilted cap-weight (e.g., Fama–French value), and niche strategies (currency-hedged small-cap emerging markets). If smart beta spans almost everything, the term means absolutely nothing.[12]

Our findings suggest that smart beta strategies cannot be replicated with simple factor tilts. If investors assume otherwise, we ignore the fact that the original smart-beta strategies generate alpha by breaking the link between price and portfolio weights. While a smart beta strategy *has* factor tilts, it truly offers much more because it delivers different return and portfolio characteristics from those simple factor tilts, and it delivers alpha net of the factor tilts and net of the Fama–French four- or five-factor regressions. Investors who might think smart beta is nothing more than simple factor tilts should be cautioned by the point we made earlier—although all Rolexes are watches, not all watches are Rolexes.

The appendix is available on our website at www.researchaffiliates.com.

Table 7. Top 10 Holdings of Smart Beta Strategies and Their Factor-Replicated Portfolios, as of June 2016

Panel A. Fundamental Index and Factor-Replicated Portfolio

	Fundamental Index		Factor-Replicated Portfolio	
Rank	Company	Weight	Company	Weight
1	Exxon Mobil	3.1%	Berkshire Hathaway	3.8%
2	Walmart	2.2%	Apple	2.7%
3	Chevron	2.1%	JPMorgan Chase	2.7%
4	AT&T	1.9%	Chevron	2.1%
5	Berkshire Hathaway	1.8%	Alphabet	2.0%
6	JPMorgan Chase	1.8%	Bank Of America	1.7%
7	General Electric	1.6%	Exxon Mobil	1.6%
8	Apple	1.4%	Citigroup	1.5%
9	Wells Fargo	1.4%	Wells Fargo	1.2%
10	Verizon	1.3%	General Electric	1.2%

Panel B. Equal Weight and Factor-Replicated Portfolio

	Equal Weight		Factor-Replicated Portfolio	
Rank	Company	Weight	Company	Weight
1	*Not applicable for an equal - weight strategy. All weights are +/-0.1% minor price drift between rebalancing dates.*		Apple	1.9%
2			Alphabet	1.6%
3			Berkshire Hathaway	1.5%
4			Exxon Mobil	1.2%
5			Microsoft	1.1%
6			JPMorgan Chase	1.0%
7			Amazon	0.9%
8			Wells Fargo	0.9%
9			General Electric	0.9%
10			AT&T	0.8%

Panel C: Minimum Variance and Factor-Replicated Portfolio

	Minimum Variance		Factor-Replicated Portfolio	
Rank	Company	Weight	Company	Weight
1	Newmont Mining	1.9%	Berkshire Hathaway	2.3%
2	Dollar General	1.7%	Apple	2.2%
3	Consolidated Edison	1.7%	Alphabet	2.0%
4	AT&T	1.7%	JPMorgan Chase	1.6%
5	Dollar Tree	1.7%	Exxon Mobil	1.6%
6	IBM	1.6%	Microsoft	1.6%
7	Verizon	1.6%	Amazon	1.3%
8	American Tower	1.6%	Chevron	1.3%
9	General Mills	1.6%	General Electric	1.2%
10	Walmart	1.6%	Johnson & Johnson	1.2%

Source: Research Affiliates, LLC, based on data from CRSP and Compustat.

Endnotes

1. The Fundamental Index and equal-weight strategies are rebalanced annually at the beginning of January. The minimum-variance strategy simulation is based on the MSCI USA Minimum Volatility Index methodology to employ a constrained optimization on the US Large + Mid-Cap universe to minimize volatility. Constraints include minimum and maximum constituent, country, and sector weights, as well as turnover. The optimization is recomputed semi-annually.

2. Annualized average returns are measured using monthly returns from the Russell 1000 Value Total Return Index, S&P 500 Total Return Index, and FTSE RAFI US 1000 Index. All returns are measured over the period January 1, 2006, to February 28, 2017.

3. For example, a Fundamental Index portfolio based on book value will weight every stock by its book value, which is equivalent to weighting a stock by its price times its relative book-to-price ratio. Classic value indices simply throw out the growth stocks and capitalization weight the value stocks, as does the Fama–French value factor portfolio.

4. For more details, please refer to Brandhorst (2006) and Asness et al. (2015).

5. There are various ways to avoid look-ahead bias. This expanding regression methodology will eventually converge to estimating full-sample factor betas toward the end of our data sample. Alternatively, we could have used a rolling-window framework to better capture the fact that factor betas are time varying. Our goal is to replicate a smart beta strategy's returns by constructing a factor tilt portfolio in each month based on the information available to investors at that point in time. Choosing between methodologies is a modeling choice. What we gain in capturing a more dynamic factor tilt from rolling-window regressions, we lose by estimating the betas less precisely on fewer observations. In unreported results, "dynamic" factor-tilt portfolios constructed from rolling regressions generate even higher turnover, because replicated portfolio weights move around more with the dynamic factor betas, resulting in even greater turnover and worse returns net of trading costs.

6. The expanding window regression methodology used to prevent look-ahead bias in the replicated portfolios will generate slightly different in-sample factor loadings for these portfolios, by construction. These factor loadings would be equal to the factor loadings of the smart beta strategies, and the market betas would be exactly equal to one, if they were instead estimated once in sample.

7. The discount is measured by taking the average of the ratios of the portfolio's P/E, P/B, P/S, and P/D to the market's respective valuation ratio. A value less than one means the portfolio is trading at a discount relative to the market.

8. Trading costs are calculated based on the Aked and Moroz (2015) trade cost model. The model assumes a 30 bp price impact per 10% of average daily volume consumed by the portfolio turnover. We appreciate and acknowledge the help of Alex Pickard in computing trading costs and capacity.

9. A reader could easily quibble with our methodology for calculating trading costs. It's harder to contest the notion that the turnover is five times as high, with much heavier use of illiquid and thinly traded small stocks in the replicating portfolios than in the standard Fundamental Index. Do we reach the point where 100 bps of damage is done at $10 billion of AUM? Or is trading easier than we suggest, and the threshold for this magnitude of damage is $25 billion? Trading costs are squishy. The relative magnitude of the costs is probably about right; the threshold at which these costs are reached is arguable. The costs could also be worse and the capacity lower than we suggest. Ouch.

10. We report capacity assuming the portfolios are rebalanced quarterly. Monthly smoothing of trading (same trades spread over three months) should boost capacity by about 70%, and weekly rebalancing should double it again. Consequently, these figures all offer room for improvement.

11. For economy of space, we show only the full replication portfolios, with long–short replication. The long-only replication portfolios—at least for the top 10 holdings—look rather similar. None of the short positions is large enough to be included in the top 25 holdings, let alone the top 10.

12. In a recent and most amusing example, etfDB.com published a summary early in 2017 of the 25 largest smart beta ETFs. The two largest were the Russell 1000 Value and Russell 1000 Growth ETFs. Suppose a newcomer to the smart beta landscape decided to invest in the two largest just to get a "toe in the water." Doing so they would be buying the Russell 1000—the market!

References

Aked, Michael, and Max Moroz. 2015. "The Market Impact of Passive Trading." *Journal of Trading*, vol. 10, no. 3 (August):1–8.

Arnott, Robert D., Jason Hsu, Vitali Kalesnik, and Phil Tindall. 2013. "The Surprising Alpha from Malkiel's Monkey and Upside-Down Strategies." *Journal of Portfolio Management*, vol. 39, no. 4 (Summer):91–105.

Asness, Clifford, Andrea Frazzini, Ronen Israel, and Tobias Moskowitz. 2015. "Fact, Fiction, and Value Investing." *Journal of Portfolio Management*, vol. 42, No.1 (Fall):34–52.

Brandhorst, Eric. 2006. "Fundamentals-Weighted Indexing Offers New Insight on Value Investing." State Street Global Advisors White Paper, January.

ETFdb.com. 2017. "Smart Beta ETF List." May 10.

Frazzini, Andrea, and Lasse Heje Pedersen. 2014. "Betting Against Beta." *Journal of Financial Economics*, vol. 111, no. 1 (January):1–25.

Disclosures