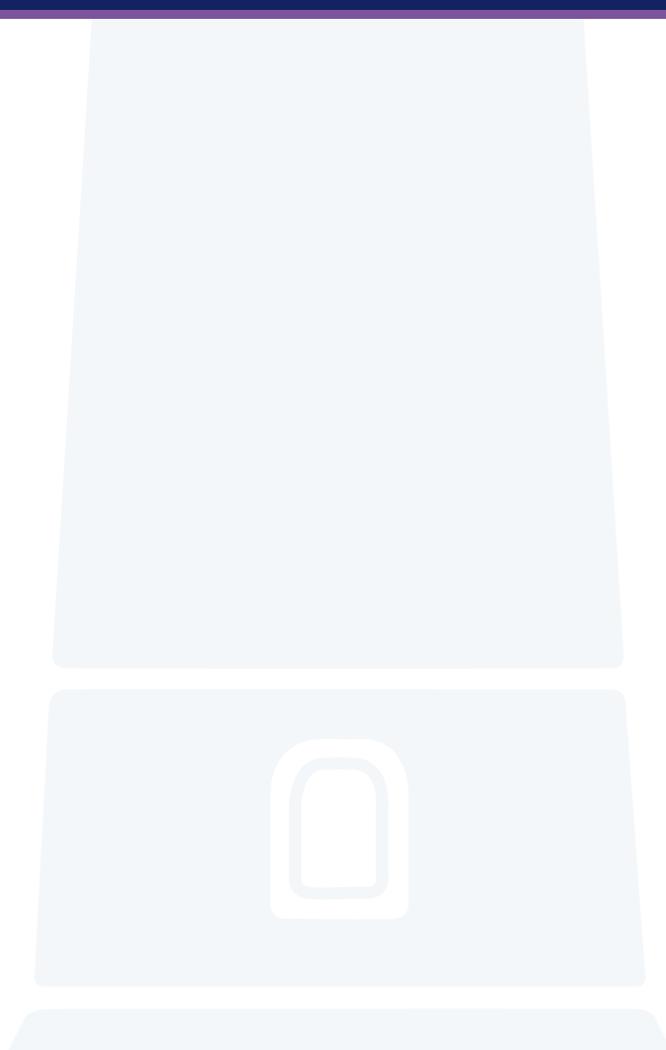# Smart Beta, Alternative Beta, Exotic Beta, Risk Factor, Style Premia, and Risk Premia Investing:

Data Mining, Arbitraged Away, or Here to Stay?

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M A N A G E M E N T

Smart Beta, Alternative Beta, Exotic Beta, Risk Factor, Style Premia, and Risk Premia Investing:

Data Mining, Arbitraged Away, Or Here To Stay?

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Executive Summary

- Smart beta (also known as alternative beta, exotic beta, risk factor, style premia, risk premia investing) is one of the most popular, cutting-edge investment products available today. As with other investment products, the largest risk confronting investors underwriting smart beta products is what to assume about returns on a *prospective* basis.

- Smart beta products have a few key features that make the "returns on a prospective basis" issue unique, interesting, and potentially problematic. First, there's a heavy reliance on historical backtesting, and "data mining" could taint any backtest. Secondly, unlike the historical backtest time period, the core of the smart beta strategy is *currently* widely known and available in the public domain. As a strategy moves along the life cycle from proprietary/private to public, some portion of the forward-looking return will likely be arbitraged away and, thus, not available to *new* investors. Both effects, data mining and arbitrage, could lead to a prospective expected return that is *lower* than the historical backtest results.

- This paper estimates the combined data mining and arbitrage effects and, consequently, provides relevant information for "correcting" the backtested results. The process for measuring the combined effects involves identifying the most important smart betas from the distant past (~25 years ago), measuring the out-of-sample performance, and comparing the out-of-sample results to the backtests (i.e. in-sample results). The selection of smart betas and the out-of-sample period are identified by Eugene Fama's famous December 1991 "Efficient Capital Markets: II" paper.

- Conservatively, the out-of-sample results suggest a 58% reduction when correcting the backtested realized average returns. When looking at a risk-adjusted portfolio measure, such as the Appraisal Ratio, the reduction is larger in magnitude at 71%. A more optimistic interpretation of the results would decrease the average return and Appraisal Ratio reductions to 30% and 40%, respectively. Under both interpretations, conservative or optimistic, the size of the performance reduction is material.

Introduction

Given smart beta's popularity among investors and asset managers, people ask me about this strategy (also known as alternative beta, exotic beta, risk factor, style premia, risk premia investing) all the time. The number one question I receive is: what should an investor expect regarding returns generated from smart beta strategies (e.g. value, momentum, carry, low volatility, etc.), and how does it compare to the historical backtested results that normally accompany smart beta strategies?

Unfortunately, like the rest of you, I just don't know. I have no crystal ball. We'd have to wait as much as 25 years to gain insights on the true return properties of the various smart betas available today. Robust backtests and theory are helpful for understanding the return properties of smart beta strategies, but they can't completely mitigate the risks associated with unintended "data mining" - continuously searching for return predictability in a fixed historical record that inevitably mischaracterizes randomness as a systematic factor deserving of a standalone, prospective risk premium.

Even if data mining weren't an issue, historical backtests may provide an inaccurate depiction of the future if the factor (e.g. value, momentum, carry, low volatility, etc.) in question is now *publicly* known by the investment community with many products available to *access* it. Profitable strategies that become public attract capital and that additional capital tends to push prices back to fair value. In other words, part of the observed historical risk premium reported in the backtest might already be arbitraged away and, thus, not available to investors looking to make an allocation today.
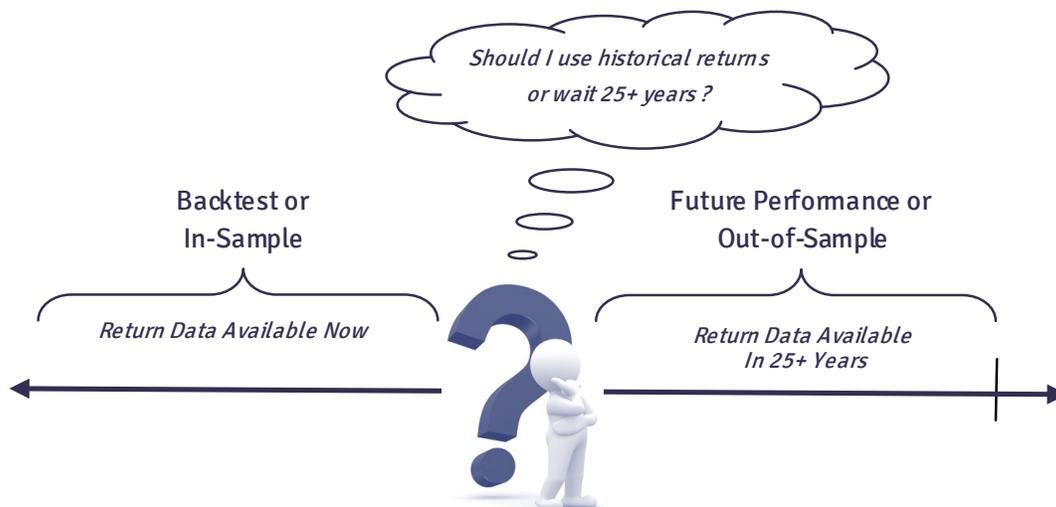
So how do we assess the impact of these critical concepts – data mining and arbitrage? Is waiting 25 years really the only answer? In order to account for the detrimental effects of data mining and arbitrage, should investors cut the historical backtested risk premium in half and use that as their forward-looking return estimate? Or is this approach too arbitrary? Sounds arbitrary to me.

While there's no silver bullet here, I can help move the debate forward if we can answer the following questions: Is there any way to credibly run an ~25 year out-of-sample test on the most popular smart betas from the early 1990s by going back in an *unbiased, documented* time capsule? What were the popular smart betas ~25 years ago? How were the smart betas constructed? How do the last 25 years of "out-of-sample" results, i.e. smart beta returns earned by hypothetical investors from the early 1990s through 2015, compare to the backtested results that would have been available and marketed to investors in the early 1990s? Did the out-of-sample results decrease as a result of data mining and/or arbitrage? If so, by how much? What are the implications for *today's* large stable of backtested only smart beta products and their prospective investors? Should today's investors expect a similar decline (if any) over the *next* 25 years? I think I figured out a way to credibly implement this. Stay tuned.

Before leaving this section, I want to take a quick detour down "nomenclature lane." Generally speaking, I think of smart beta as being interchangeable with alternative beta, exotic beta, risk factor, style premia, and risk premia investing. Somewhat confusing? Yes. It is what it is. As you may have noticed, to keep things simple and efficient, I'm going to *arbitrarily* ordain smart beta as my alias of choice throughout the paper. At times, I might slip in "factor" as a substitute for smart beta. There is no science behind my choice. Back to the paper.

Figure 1

Should I use historical returns or wait 25+ years?

Backtest or In-Sample

Future Performance or Out-of-Sample

Return Data Available Now

Return Data Available In 25+ Years

What is Smart Beta? A Brief Review

While everyone can have their own nuanced definition, in this paper, smart beta is going to be any trading strategy that has the following characteristics:

1) The trading strategy buys, sells, and forms portfolios based on observable, available market and/or accounting characteristics, such as: past returns (momentum), price multiples (value), realized volatility (low vol), yield (carry), accounting return on equity (profitability), accounting asset growth rate (investment), etc. This excludes the value-weighted market portfolio for any asset class (or groups of asset classes).

2) The trading strategy is systematic in nature, i.e. the logic behind the buying and selling can be clearly written out and implemented.

3) The trading strategy and associated backtested returns are, generally speaking, available in the *public* domain.

Characteristics "1)" and "2)" above also define a classic, active manager that utilizes a systematic/quantitative process. This manager's strategy isn't necessarily smart beta because his systematic trading signals and process could be *proprietary*. However, once his signals and process become *publicly* known (characteristic "3)"), the same manager's strategy becomes smart beta overnight. In other words, think of smart beta as a systematic/quantitative manager who only uses publicly available, widely known trading signals.

It's important to note that smart beta can be run in most markets (e.g. equities, fixed income, etc.) at the security level (e.g. IBM vs Apple stock) or at the index level (e.g. S&P 500 vs FTSE). Today's piece will be focusing on equity security selection strategies. More to come.

A Credible, Unbiased and Documented Backtest

For this paper to provide maximum value, I need to convince you that my process for selecting/constructing the smart betas, choice of in-sample time period (backtest), and choice of out-of-sample time period (actual investor experience) is not arbitrary. In other words, I need to convince you that my approach is credible, unbiased, and documented ...to the best of my ability.

My dissertation advisor and 2013 Nobel Prize recipient, Eugene Fama, plays a central role in my approach. How? Eugene Fama is unquestionably one of the leading researchers of equity security selection (i.e. smart beta) strategies. In December 1991, Eugene Fama published his Efficient Capital Markets Sequel paper (i.e. "Efficient Capital Markets: II"), which is a famous, well-respected survey paper that covered relevant topics for the market efficiency debate. In the security selection (i.e., smart beta) section of the paper, he identifies and focuses on 4 factors above and beyond general market beta that cross-sectionally predict returns:

- **Equity market capitalization** ("ME", Banz 1981): small stocks outperform large stocks
- **Earnings-to-price** ("EP", Basu 1977): high EP stocks outperform low EP stocks
- **Debt-to-equity** ("DE", Bhandari 1988): high DE stocks outperform low DE stocks
- **Book-to-market** ("BEME", Fama French 1992): high BEME stocks outperform low BEME stocks

Out of all the potential published factors (smart betas) in the historical published record at the time, Eugene Fama, the Michael Jordan of equity security selection research, chose to highlight these four as the most important, which can be thought of as one size factor and three versions of a value factor[i].

As a result, these 4 factors (smart betas) are the focus of this paper. Importantly, the characteristics that define the factors will be constructed in a manner as consistent as possible with the original published papers cited in Fama's survey article[ii]. Additionally, the in-sample backtest will be defined by the time period studied in the original published paper[iii]. The out-of-sample time period will start in 1992 – the date following Fama's Efficient Markets Sequel paper publication – through 2015. In my opinion, the degrees of freedom for data mining have been minimized[iv].

Figure 2
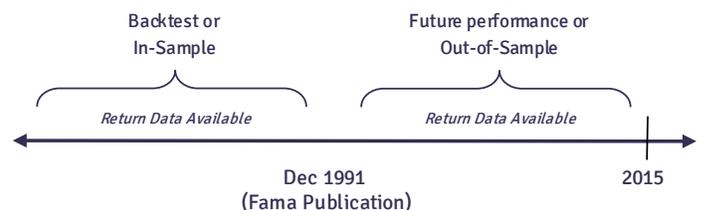
Factor Formation and Key Performance Metrics

In order to calculate the returns, we need to spell out and implement the systematic trading strategies associated with each smart beta factor (i.e. the "1)" and "2)" characteristics from an earlier section of this paper). This is sometimes known as the factor formation process. The smart beta factor formation process is identical for each of the 4 factors. First, stocks are sorted into quintiles (i.e. 5 portfolios) based on the characteristic of interest (ME, EP, DE, or BEME). Within each quintile, a value-weighted portfolio return is calculated for each month. Then, a long-short portfolio is formed going long the top quintile portfolio (Portfolio #5) and short the bottom quintile (Portfolio #1). This methodology is considered standard in the research literature[v].

Let's do a quick example using a value factor, book-to-market (EP: earnings-to-price, DE: debt-to-equity). The factor is long high book-to-market (EP, DE) stocks and short low book-to-market (EP, DE) stocks. If high book-to-market stocks outperform low book-to-market stocks, this factor will properly pick up the effect.

Figure 3
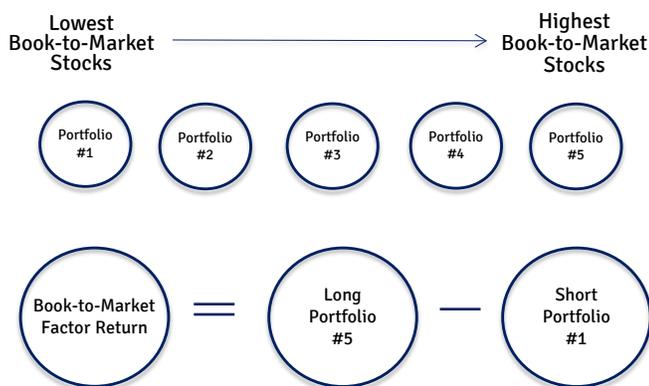
There is one caveat with respect to defining the size factor (ME). Since the thesis is that small stocks outperform large stocks, for the size factor, we reverse the order of the long-short portfolio: we go long the *bottom* quintile portfolio (Portfolio #1, small cap stocks) and short the *top* quintile portfolio (Portfolio #5, large cap stocks). For ease of interpretation, the factors are defined in a manner such that the average return is expected to be positive.

Figure 4
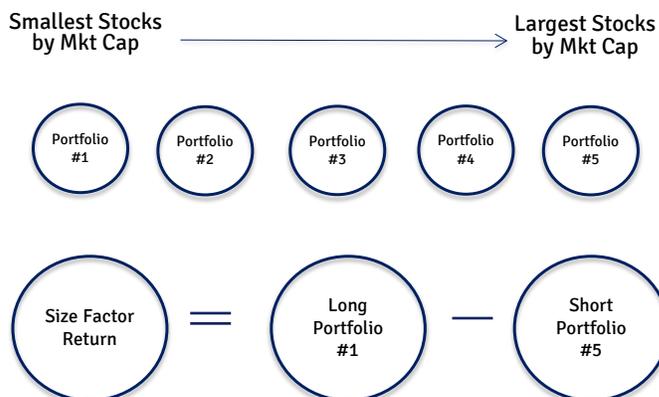
Now that we have a time series of monthly returns for each of the 4 factors (smart betas), we will focus our attention on 4 key performance metrics when comparing the in-sample (backtested) and out-of-sample (actual investor experience) results: average return, Sharpe Ratio, alpha (relative to the U.S. stock market), and Appraisal Ratio (also known as alpha Sharpe Ratio or beta-adjusted Sharpe Ratio). Each metric has a slightly different interpretation.

> ...backtests and theory are helpful for understanding the return properties of smart beta strategies, but they can't completely mitigate the risks associated with unintended "data mining"...

The first two metrics, average return and Sharpe ratio, take more of a "silo" view...as if the investor were going to allocate 100% of his wealth to a particular factor (smart beta). The second two metrics, alpha and Appraisal ratio, take a "portfolio" view...how valuable is this factor if I already hold the U.S. stock market? Additionally, average return and alpha are not adjusted for risk (volatility). The risk-adjusted measures, Sharpe Ratio and Appraisal Ratio, are more relevant to the extent leverage is available. My favorite is the Appraisal Ratio since it takes a portfolio view and risk adjusts. Why? As I've shown in previous research (https://www.evanstoncap.com/docs/news-and-research/evanston-capital-research---appraisal-ratio.pdf), the factor (smart beta or any investment) with the highest Appraisal Ratio (measured relative to the investor's current portfolio) will improve the portfolio's overall risk-adjusted return (i.e. Sharpe Ratio) the most. Modern portfolio theory has taught us to evaluate investments in the context of the entire portfolio, and the Appraisal Ratio does just that.

All 4 performance metrics will be calculated for the in-sample (original publication period) and out-of-sample period (1992 - March 2015). Then, the out-of-sample results (actual investor experience) will be compared to the in-sample (backtest) results. How much lower (if at

all) are the out-of-sample results? The difference between the out-of-sample and in-sample results provides an estimate of the *combined* data mining and arbitrage effects discussed earlier. In other words, if the out-of-sample results are lower, the original results were partially data mined and/or the original results were real but have been partially arbitraged away since becoming *publicly known* and *available*.

For completeness, I will also test for statistical significance: can we statistically reject the hypothesis that the true out-of-sample metric is different than the true in-sample metric? Perhaps the realized differences are driven by chance/luck – not data mining or arbitrage. Note, however, the statistical tests will lack power[vi]. In other words, even if the in-sample and out-of-sample results are truly different, we're unlikely to uncover statistical significance without having a lot more data. Keep this in mind when interpreting the results in the tables below.

TABLE 1: Size Factor ("ME"), Banz (1981)

	In-Sample (1936-1975)*	Out-of-Sample (1992-2015)	Ratio of Out-of-Sample to In-Sample	Out-of-Sample Less In-Sample
Monthly:				
Average Return	0.43%	0.31%	70.26%	-0.13%
Alpha	0.10%	0.19%	186.34%	0.09%
Sharpe Ratio	0.08	0.07	83.88%	-0.01
Appraisal Ratio	0.02	0.04	203.53%	0.02

TABLE 2: Debt-to-Equity Factor ("DE"), Bhandari (1988)

	In-Sample (1951-1979)*	Out-of-Sample (1992-2015)	Ratio of Out-of-Sample to In-Sample	Out-of-Sample Less In-Sample
Monthly:				
Average Return	0.42%	0.17%	41.67%	-0.24%
Alpha	0.38%	0.21%	54.75%	-0.17%
Sharpe Ratio	0.15	0.03	21.91%	-0.12
Appraisal Ratio	0.14	0.04	28.63%	-0.10

TABLE 3: Book-to-Market Factor ("BEME"), Fama and French (1992)

	In-Sample (1963-1990)*	Out-of-Sample (1992-2015)	Ratio of Out-of-Sample to In-Sample	Out-of-Sample Less In-Sample
Monthly:				
Average Return	0.48%	0.28%	57.89%	-0.20%
Alpha	0.51%	0.30%	59.60%	-0.21%
Sharpe Ratio	0.14	0.08	56.96%	-0.06
Appraisal Ratio	0.15	0.09	58.37%	-0.06

TABLE 4: Earnings-to-Price Factor ("EP"), Basu (1977)

	In-Sample (1957-1971)*	Out-of-Sample (1992-2015)	Ratio of Out-of-Sample to In-Sample	Out-of-Sample Less In-Sample
Monthly:				
Average Return	0.63%	0.37%	58.11%	-0.26%
Alpha	0.65%	0.45%	69.19%	-0.20%
Sharpe Ratio	0.22	0.11	49.37%	-0.11
Appraisal Ratio	0.23	0.14	59.68%	-0.09

Time period studied in original publication. Annualized results in Appendix.

Results

For each of the 4 factors, the in-sample (backtest), out-of-sample (actual investor experience), and comparison results are reported in Tables 1, 2, 3, and 4. Not surprisingly, all 4 factors have positive average monthly returns, Sharpe Ratios, alphas, and Appraisal Ratios during the in-sample period. Now to the key results...what happens during the out-of-sample period, 1992 – 2015? Excluding a few exceptions for size (ME), all of the performance metrics decrease during the out-of-sample period, suggesting that data mining and arbitrage play a material, economically significant role.

On a ratio basis, the out-of-sample average returns tend to be between 42% to 70% of the in-sample results. On an absolute basis, the largest (smallest) monthly average return reduction occurs for EP (ME), going from 0.63% to 0.37% (0.43% to 0.31%).   On a ratio basis, the out-of-sample alphas tend to be between 55% to 186% (55% to 69% excluding ME) of the in-sample results. On an absolute basis, the largest (smallest) monthly alpha reduction occurs for BEME (ME), going from 0.51% to 0.30% (0.10% to 0.19%). On a ratio basis, the out-of-sample Sharpe Ratios tend to be between 22% to 84% of the in-sample results. On an absolute basis, the largest (smallest) monthly Sharpe Ratio reduction occurs for DE (ME), going from 0.15 to 0.03 (0.08 to 0.07). Lastly, on a ratio basis, the out-of-sample Appraisal Ratios tend to be between 29% to 204% (29% to 60% excluding ME) of the in-sample results. On an absolute basis, the largest (smallest) monthly Appraisal Ratio reduction occurs for DE (ME), going from 0.14 to 0.04 (0.02 to 0.04).

> ...historical backtests may provide an inaccurate depiction of the future if the factor in question is now *publicly* known by the investment community with many products available to *access* it.

On a ratio basis, the out-of-sample alpha and Appraisal Ratio for size (ME) are actually higher. However, it's important to note that the in-sample alpha and Appraisal Ratio results for size (ME) are *close to zero* (Monthly: 0.10% alpha, 0.02 Appraisal Ratio), which brings up two issues. First, the in-sample results are arguably not economically meaningful, and, thus, not worthy of a comparison in the first place. Secondly, making "proportional" comparisons (i.e. calculating a ratio) to a number close to zero can be misleading since one is effectively dividing by a number close to zero. In this case, economically insignificant changes in the denominator can lead to massive swings in the calculated out-of-sample to in-sample ratio. Consequently, I would take the size (ME) alpha and Appraisal Ratio comparison results with a grain of salt.

Is it possible the observed out-of-sample reductions occurred by

chance and, thus, have nothing to do with data mining or arbitrage? Yes. In fact, according to the results in Table A-5 (in the appendix), none of the out-of-sample results are *statistically* different than the in-sample results. All of the t-statistics are less than 2 (in absolute value), which is the typical marker for statistical significance. However, as stated earlier, these statistical tests lack power, i.e. were unlikely to detect statistical differences without a lot more data.

Although my approach is credible, unbiased, and documented…to the best of my ability, there are a few caveats current investors need to consider when interpreting the results. First, the 4 smart betas identified by Fama were originally published at different times. The earlier ones, such as EP (1977), had more time to attract capital and push prices closer to fair value before the official out-of–sample period started (1992). In contrast, the later ones, such as BEME (1992), might be earlier in their arbitraged away life cycle once the out-of-sample period begins. One could argue the results presented here are more relevant for those smart betas today at a similar point in their arbitraged away life cycle. Secondly, due to financial innovation, the arbitrage away effect shows up in prices much faster today than in 1992. Easily accessible, smart beta-motivated exchange traded funds (ETFs) and mutual funds are now everywhere. This wasn't the case back in 1992. As a result, one could argue that the out-of-sample results presented here may be too optimistic for current investors.

Bottom Line

Smart beta (also known as alternative beta, exotic beta, risk factor, style premia, risk premia investing) is currently one of the most popular, cutting-edge investment products available today and, in my opinion, is legitimately here to stay in one form or another. As with other investment products, the largest risk confronting investors underwriting smart beta products is what to assume about returns on a *prospective* basis.

In comparison to other investments, smart beta products have a few key features that make the returns on a prospective basis issue unique, interesting, and potentially problematic. First, there's a heavy reliance on historical backtesting, which gives investors a sense of clarity – akin to "test driving" the strategy before making an actual investment. However, data mining could taint any backtest. Secondly, unlike the historical backtest time period, the core of the systematic strategies is *currently* widely known and available in the public domain. As a strategy moves along the life cycle from proprietary/private to public, some portion of the forward-looking return will likely be arbitraged away and, thus, not available to *new* investors. Not fully appreciating these features can lull investors into a false sense of confidence about future return performance.

So what's an investor supposed to do beyond critically analyzing the backtest and theory behind the smart beta? Although there's no elegant solution, the investor needs to "haircut", i.e. reduce, the backtested performance results when formulating forward-looking return assumptions. Assuming the backtest methodology and theory components pass the "sniff test" (a must but not the focus of today's piece), the haircut could be large and meaningful.

While far from perfect, my ~25 year out-of-sample ratio results suggest a conservative haircut of 58% (= 100% - 42%) when correcting the backtested realized average returns. When looking at a risk-adjusted portfolio measure, such as the Appraisal Ratio, the conservative haircut number is larger in magnitude at 71% (= 100% - 29%). A more optimistic interpretation of the results would reduce the average return and Appraisal Ratio haircuts to 30% (= 100% - 70%) and 40% (= 100% - 60%), respectively. Even though there is a range in the magnitude of the conservative and optimistic haircuts, one thing is crystal clear: under both interpretations, the size of the haircut is material.

Is the spirit of my equity security selection results relevant for smart beta strategies in other markets or using indices? Probably…to some extent, but I don't know exactly and obviously can't prove it. But let's step back from the numbers for a moment. The concepts and implications of "backtests and data mining" and "publicly known and arbitrage" make economic intuitive sense[vii]. Thus, I feel comfortable stating that the smart beta haircuts could be material for all markets… if I were a betting man. Keep this in mind when underwriting smart beta or alternative beta, exotic beta, risk factor, style premia, risk premia strategies, etc. - whatever name it may be - good luck!

Appendix

TABLE A-1: Size Factor ("ME"), Banz (1981)

	In-Sample (1936-1975)*	Out-of-Sample (1992-2015)
Annualized:		
Average Return	5.21%	3.66%
Alpha	1.21%	2.26%
Sharpe Ratio	0.28	0.23
Appraisal Ratio	0.07	0.15

TABLE A-2: Debt-to-Equity Factor ("DE"), Bhandari (1988)

	In-Sample (1951-1979)*	Out-of-Sample (1992-2015)
Annualized:		
Average Return	5.02%	2.09%
Alpha	4.53%	2.48%
Sharpe Ratio	0.52	0.11
Appraisal Ratio	0.47	0.14

TABLE A-3: Book-to-Market Factor ("BEME"), Fama and French (1992)

	In-Sample (1963-1990)*	Out-of-Sample (1992-2015)
Annualized:		
Average Return	5.81%	3.36%
Alpha	6.14%	3.66%
Sharpe Ratio	0.48	0.27
Appraisal Ratio	0.51	0.30

TABLE A-4: Earnings-to-Price Factor ("EP"), Basu (1977)

	In-Sample (1957-1971)*	Out-of-Sample (1992-2015)
Annualized:		
Average Return	7.57%	4.40%
Alpha	7.83%	5.42%
Sharpe Ratio	0.78	0.38
Appraisal Ratio	0.80	0.48

*Time period studied in original publication.

TABLE A-5: Are the Results Due to Chance? Testing for Statistical Significance

T-Statistic, Null: In-Sample= Out-of-Sample			
	ME	DE	BEME	EP
Average Return	-0.35	-0.69	-0.71	-0.90
Alpha	0.25	-0.48	-0.72	-0.68
Sharpe Ratio	-0.17	-1.45	-0.73	-1.15
Appraisal Ratio	0.28	-1.19	-0.75	-0.94

End Notes

[i] Cliff Asness of AQR has fairly pointed out that Eugene Fama has potential biases. For example, the momentum factor was known in 1991, but was not mentioned in Fama's 1991 Efficient Capital Market's Sequel publication. To be fair to Fama, the investment community's understanding of momentum was less mature relative to the other factors at the time. As momentum became more commonplace in the mid 1990s, it was incorporated into Fama's research.

[ii] Basu, 1977, "Investment Performance of Common Stocks in relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis"; Banz, 1981, "The Relationship Between Return And Market Value Of Common Stocks"; Bhandari, 1988, "Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence"; Fama and French, 1992, "The Cross Section of Expected Stock Returns".

[iii] Unless the data is unavailable.

[iv] Pontiff and Maclean (2015, "Does Academic Research Destroy Stock Return Predictability?") look across all published equity security selection factors across all out-of-sample timeframes. In contrast, this piece focuses only on the most important factors (as determined by Eugene Fama) with one, long, consistent, out-of-sample timeframe.

[v] Excluding the DE factor, all of the return data was obtained from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. All of the data required for the DE factor was obtained from CRSP and COMPUSTAT.

[vi] Statistical power is defined as the probability that the test correctly rejects the null hypothesis when the alternative hypothesis is true.

[vii] For more information on the "publicly known and arbitrage" topic, refer to Asness, 2015, "How Can a Strategy Still Work If Everyone Knows About It?"

About the Authors

Mr. Hecht is a Managing Director, Senior Investment Strategist at Evanston Capital Management, LLC ("ECM"). Prior to joining ECM, Mr. Hecht served in various portfolio manager and strategy roles for Allstate Corporation's $35 billion property & casualty insurance portfolio and $4 billion pension plan. He also had the opportunity to chair Allstate's Investment Strategy Committee, Global Strategy Team, and Performance Measurement Authority. Mr. Hecht also served as an Assistant Professor of Finance at Harvard Business School. His research and publications cover a variety of areas within finance, including behavioral and rational theories of asset pricing, liquidity, capital market efficiency, complex security valuation, credit risk, and asset allocation. Mr. Hecht previously served at investment banks J.P. Morgan and Hambrecht & Quist, and as a consultant for State Street Global Markets. Mr. Hecht has a bachelor's degree in Economics and Engineering Sciences from Dartmouth College and an MBA and Ph.D. in Finance from the University of Chicago's Booth School of Business.

Mr. Du is a Ph.D. candidate in finance at Northwestern University. His research focuses on empirical asset pricing. His job market paper studies the relationship between web visits to SEC-filings of insider trades and post-filing stock returns. The main finding of the paper is that when the filing of insider purchases (sales) receive more web visits within the first one minute of filing-time, the hourly, daily, and weekly post-filng stock returns are more positive (negative). Prior to his Ph.D. studies, he worked as a junior trader in the credit derivative market in Hong Kong. He also interned at UBS, China Investment Corporation, and the People's Bank of China. Mr. Du got his master's degree of financial engineering from UC Berkeley and Bachelor's degree in finance from Tsinghua University.

Evanston Capital Management, LLC

Founded in 2002, Evanston Capital Management, LLC is an alternative investment firm with approximately $5.0 billion in assets under management as of March 1, 2016. ECM has extensive experience in hedge fund selection, portfolio construction, operations and risk management. The principals collectively have more than 75 years of hedge fund investing experience, and the firm has had no turnover in senior-level investment professionals since inception. ECM strives to produce superior risk-adjusted returns by constructing relatively concentrated portfolios of carefully selected and monitored hedge fund investments.

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