Integrity in Investing:
How Smart Is Planning with "Smart-Beta" Strategies?

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PROFESSIONAL FINANCIAL
Consultative Wealth Management

> *"The curious task of economics is to demonstrate to men how little they know about what they imagine they can design."*
> – **Friedrich Hayek**, Nobel laureate economist & philosopher

This is part of a series exploring integrity for informed investment management decisions

Key takeaways:

- Research supporting low-volatility fund strategies does not stand up to careful statistical testing

- Extensive diversification within dimensional asset classes drives more reliable planning outcomes

- A high standard of research is needed to minimize numerous spurious factor correlations

- Structured portfolios focused on dimensional asset classes create a robust management framework

Following the early part of this year's market turbulence, after a "Brexit" vote supposedly portending a banking and market crisis, the Volatility Index ("VIX")—a measure of how much investors pay to protect their stock values, and thus an index of market fear—has fallen faster than at any time on record, and is at an historic low.[1] Global equity markets rose quickly after the Brexit vote, contrary to dire predictions of many commentators. As the *Wall Street Journal* observed about the low VIX in a *Wealth Advisor Daily Briefing*, "Nothing to fear but the absence of fear."[2]
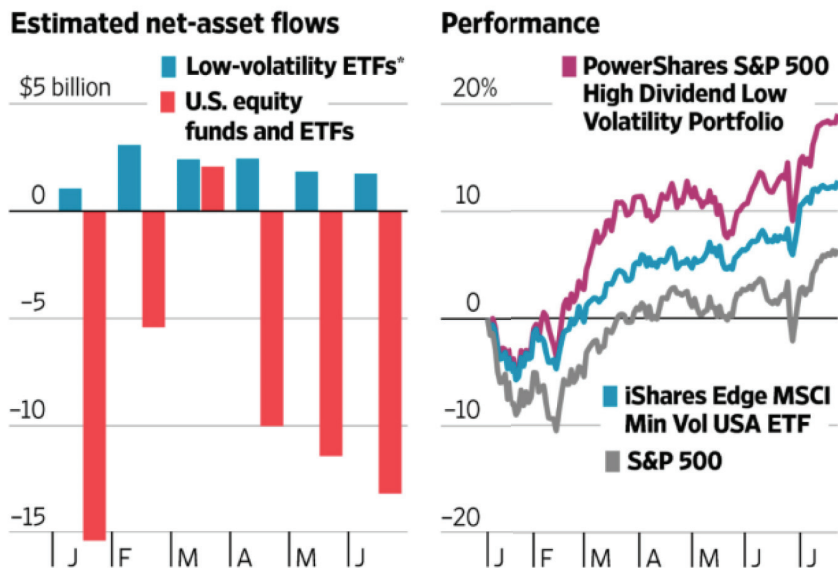
Also this year investors have poured billions of dollars into specialized "smart-beta" funds promising to reduce market swings, highlighting an uneasy anxiety that persists after seven years of broad U.S. market recovery. "Low-volatility" funds attract investors nearing or in their retirement years because yields on bonds, the preferred choice of most retirees, are historically low. Since 2009 only 6 percent of the stock and mutual fund gains have been due to net money flows. The remaining was price appreciation occurring as interest rates declined as central banks worldwide printed over $8 trillion.[3] So-called low-volatility funds are designed to fluctuate less than the stock market—not rising as high in price during rallies but designed not to fall as far during selloffs. In **Exhibit 1** we see that a net $12.5 billion was added to the top five low-volatility ETFs from January to June 2016, even as nervous

investors withdrew about $52 billion from U.S. equity funds and ETFs. These ETF returns this year have handily surpassed the S&P 500 index for U.S. large stocks.

Low-volatility funds of both iShares and PowerShares have outperformed the S&P 500 by more than 9 percentage points over the past one year and kept pace with the market over the past three years. A number of academic articles of factor studies related to volatility have been published over the years. Industry research data suggests that low-volatility stocks should outperform by about 1 percent annually with about 30% less volatility. The story used to explain this outcome is that during bull markets investors tend to pay less for stocks that don't make big moves.[4] Yet investors who routinely purchase high-performance products should be cautioned that substantial

Estimated net-asset flows
- Low-volatility ETFs*
- U.S. equity funds and ETFs

Performance
- PowerShares S&P 500 High Dividend Low Volatility Portfolio
- iShares Edge MSCI Min Vol USA ETF
- S&P 500

*Top five low-volatility ETFs by flows as of June 30.

Source: Morningstar Direct, FactSet (performance)

allocations into a product strategies that originated only in 2011, while avoiding the known high volatility of stocks, could instead be impacted by an unknown market risk that could threaten the very income flow they are so desperately seeking.

"Smart-beta" mutual funds and ETFs eschew the stock picking techniques of traditional active managers. Instead, they follow rules-based indexes that overweight stocks based on research factors statistically related to value, size, profitability, momentum as well as volatility, associated with higher risk-adjusted past returns. Assets for such ETFs have risen from about $150 billion to $450 billion in just five years. The question is which "smart-beta" funds will actually benefit investors during the *next* five years, and which will not because research was somehow uninformed.

Since the tech bust in 2000 and further poor results since the financial crisis years, conventional active managers have found that index fund families like Vanguard have become an increasingly serious career challenge. Negative publicity from the media and internet access to data since then has not helped. Much of the new wave of so-called "smart-beta" strategies could be disguised marketing efforts to rebrand quant-based strategies based on questionable "research."

"Smart-beta" strategies commonly used for funds by the financial industry also include "fundamental," equal-weight, high-dividend, high-momentum, low-beta, and high quality. Academics often do not agree with industry-applied definitions or applications of those smart-beta "factors." They all assemble portfolios other than by stock market-weighted capitalization, as do index funds. While the financial industry claims to have extensive "research," the data is often of dubious quality and for limited periods. Obviously every "factor" out there cannot out-perform market indexes. Proponents hypothesize smart-beta funds improve investor behavior, and consequently investor returns, but investing has no free lunch: by paying too much to avoid risks they see, investors could miss the returns they need to achieve.

Huge flow of money from large numbers of investors chasing hot returns, such as low-volatility EFTs, will inflate the prices of the underlying securities. That in turn attracts even more buyer money, and encourages a mini-bubble. Likely many "smart beta" strategies related to income have outperformed certain measures simply because new current cash flows coming from bonds chasing high-dividend stocks are driving security valuations higher and then even higher still.

For instance, valuations for low-volatility stock sector from 1970 to the early 2000s was half that of the overall market. Today they trade at an average of 2.8 to 2.9 times book value, or 40% more than the U.S. market historical average. Since the firms cost of capital is the investor's return, realized returns over the next five years are very likely to be much lower. As of June 2016, U.S. stock aggregate price-to-book is 1.2 for value, 3.1 for neutral (average is 2.0), but 8.9 for growth! Non-U.S. developed stock aggregate price-to-book is 0.85 for value, 1.9 for neutral, but an astonishing 4.7 for growth.[5]

## Is Volatility a Reliable Factor for Higher Returns?

Helping investors better understand the true impact of volatility on expected returns for stock market strategies is important for a long-term investment policy commitment. People invest their savings hoping to earn a rate of return above that of just holding cash in the proverbial mattress. There is ample evidence that capital markets have historically rewarded investors. For example, **Exhibit 2** illustrates how investing $1 in 1926

into diversified asset classes (if that were possible) could have translated to through the end of 2015. Nevertheless, returns of specific asset classes can be negative for days, months, and even years. After prolonged disappointment, investors become vulnerable to troubling media and internet stories about disturbing economic events, fearing how much more they may lose or miss earning.

When market volatility spikes as it did during the Financial Crisis years of 2008-2009, remaining disciplined can be even more challenging. So-called industry pundits quickly invent stores linking the latest volatility spurt to recent unfortunate events or impending "crises," pontificating poor or possibly disastrous outcomes. Their advice often is "sell now" to avoid a perceived threat, and to "buy this" to "protect" assets. But as Nobel laureate Professor Eugene Fama points out, "The onset of high volatility should be associated with price declines that increase expected returns going forward"—compensating investors for that higher volatility.[6] That is, volatility normally increases *after* prices have already declined, which increases expected returns. So pundits are actually looking backward at the data, not forward looking.

Exhibit 2: MONTHLY GROWTH OF WEALTH ($1), *1926–2015*
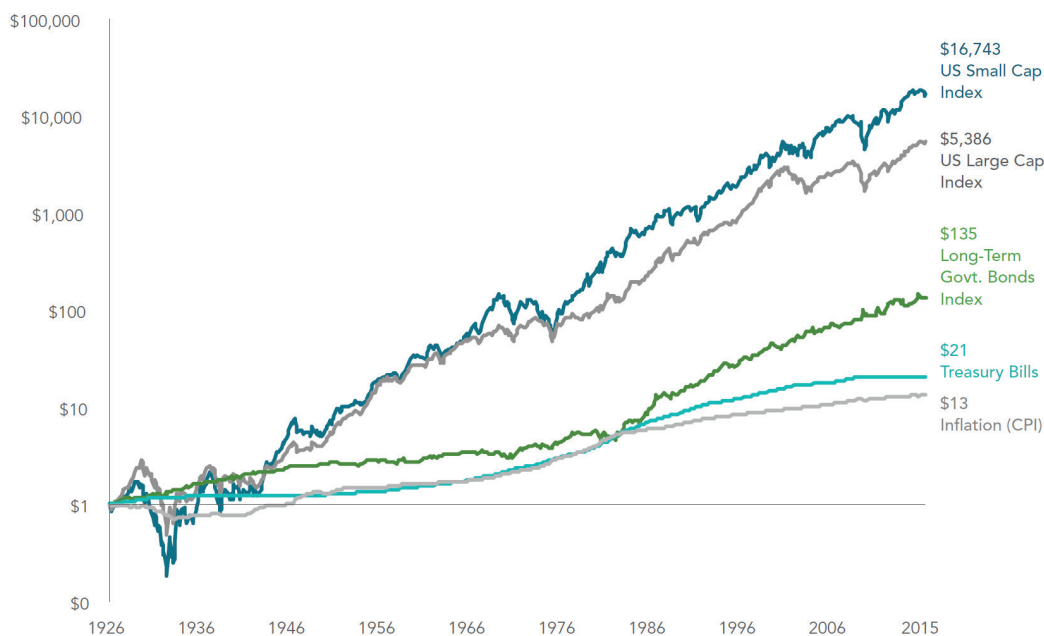
- $16,743 US Small Cap Index
- $5,386 US Large Cap Index
- $135 Long-Term Govt. Bonds Index
- $21 Treasury Bills
- $13 Inflation (CPI)

Past performance is no guarantee of future results. Indices are not available for direct investment. Their performance does not reflect the expenses associated with the management of an actual portfolio. See Index Definitions in the Appendix for more information. US Small Cap Index is the CRSP 6–10 Index; US Large Cap Index is the S&P 500 Index; Long-Term Government Bonds Index is 20-year US government bonds; Treasury Bills are One-Month US Treasury bills; Inflation is the Consumer Price Index. CRSP data provided by the Center for Research in Security Prices, University of Chicago. Bonds, T-bills, and inflation data provided by Morningstar.

Does historical stock market volatility have usable information about future returns translatable into profitable trading? Let's examine a much larger set of empirical data than that available to industry researchers to determine: (1) if significant differences in returns differ between more volatile and less volatile markets, (2) if a strategy avoiding equities in times of high volatility adds value compared to simply holding asset class allocations, and (3) if volatility levels and subsequent returns can reliably related in structuring market portfolios.

To see if stock market volatility and returns are related is simply to look at average returns across different market environments. In **Exhibit 3**, monthly returns for the entire U.S. equity market (represented by the Fama/French U.S. Total Market Index) are separated based on the previous month's standard deviation (computed using daily stock market returns). We find that average returns in months when the previous month had higher volatility (75th percentile or above) were slightly higher than when the previous month had lower volatility (25th percentile or below). But these differences in average returns have not been reliably different from zero. In other words, there does not seem to be an economically meaningful difference in average equity returns simply based on the volatility of the prior month.

Still, while average stock market returns appear similar across different levels of market volatility, is the *equity premium* (that is, the excess return over risk-free U.S. Treasury bills) also similar across different levels of volatility? **Exhibit 4** examines the average monthly returns for the U.S. equity market and risk-free T-bills from 1927 through April 2016. The 70-year data sample is further broken out into average returns for months following a

Exhibit 3: US EQUITY MARKET, *JANUARY 1927–APRIL 2016*

	Average Monthly Returns	Average Volatility in Prior Month
Low Volatility	0.98	1.95
High Volatility	1.01	7.75

Past performance is no guarantee of future results. Indices are not available for direct investment; therefore, their performance does not reflect the expenses associated with the management of an actual portfolio. US Equity Market is the Fama/French US Total Market Index. Data provided by Fama/French.

Exhibit 4: US MARKET AVERAGE MONTHLY RETURNS VS. T-BILLS, *JANUARY 1927–APRIL 2016*

	US Equity Market	T-bills
All Months	0.92	0.28
Months after High Vol. Month	1.01	0.21
Excluding Months after High Vol. Month	0.90	0.30

Past performance is no guarantee of future results. Indices are not available for direct investment; therefore, their performance does not reflect the expenses associated with the management of an actual portfolio. The costs from excessive trading or market impact is not considered in this analysis.
US Equity Market is the Fama/French US Total Market Index. Data provided by Fama/French. US Treasury Bills data provided by Morningstar.

"high volatility" month (75th percentile or above) and the remaining months.

With this more refined methodology, we now see that the average monthly equity premium **has been** higher after high volatility months. Nevertheless, the difference is not statistically different from zero—meaning we cannot say that the premium is reliably higher or lower due to volatility. The t-statistic for the equity premium difference is only 0.70. A t-statistic of at least 2.0 is necessary for a 95% degree of confidence that the result is different from zero. These results suggest looking at last month's volatility likely does not have useable information for forecasting this month's equity premium.

How would a volatility trading strategy that attempted to avoid investing in equities when volatility was high perform relative to a market portfolio asset allocation strategy? **Exhibit 5** shows returns and standard deviations for the U.S. equity market, T-bills, and a hypothetical trading strategy that bails out of equities and invests in T-bills when the previous month's volatility was high—a strategy that actively "flies to safety." If the previous month's volatility was high (75th percentile or above), the strategy invests in T-bills. If the previous month's volatility was not high, the strategy switches and invests in a U.S. equities index. We pretend trading is costless, including no market impact effect from other volatility traders employing the very same strategy, which frequently impacts the results of hedge fund managers.

Exhibit 5 still shows recent volatility and future returns have a random relationship. Consistent with previous

Exhibit 5: US VOLATILITY TRADING STRATEGY VS. ASSET ALLOCATION STRATEGY, *JANUARY 1927–APRIL 2016*

	US Equity Market	T-bills	Hypothetical "Fly to Safety" Strategy	75% US Equity Market/25% T-bills
Average Monthly Return (%)	0.92	0.28	0.72	0.76
Annualized Compound Return (%)	9.75	3.41	8.22	8.49
Annualized Standard Deviation (%)	18.66	0.88	12.21	14.00

The Hypothetical "Fly to Safety" Strategy invests in T-bills if the previous month's volatility was high (75th percentile or above). If the previous month's volatility was not high, the strategy invests in US equities. Past performance is no guarantee of future results. Indices are not available for direct investment; therefore, their performance does not reflect the expenses associated with the management of an actual portfolio. The costs from excessive trading or market impact is not considered in this analysis.

US Equity Market is Fama/French US Total Market Index. Data provided by Fama/ French. US Treasury Bills data provided by Morningstar.

studies, the relationship looks "flat." That is, recent volatility does not indicate if future returns will be "high" and does not indicate if future returns will be "low." The volatility of the "fly to safety" strategy, as measured by its standard deviation, was lower than the volatility of the U.S. equity market (12.21% vs. 18.66% annualized) over the longest period of market research data we have. This makes sense because the fly to safety strategy is securely invested in very low volatility T-bills fully one quarter of the time.

However, this lower volatility came with a cost in the form of lower returns: the fly to safety strategy had an annualized return of 8.22%, compared to 9.75% for U.S. equities (again, unrealistically assuming costless trading). Alternatively a "passive" asset allocation investing 75% in the U.S. market and 25% in T-bills would have performed similarly to the "active" fly to safety strategy. This clearly illustrates the planning benefit of a well-structured asset allocation strategy which can be customized around an investor's particular risk preferences. Asset allocation may enhance outcomes where portfolios are taxable, due to avoiding the costs of frequent trading that negatively impact returns.

What can we take away from our elementary analysis from an unbiased extended sample of market history? Put simply, we can expect volatility from stock investing. Compared to asset classes like T-bills or bonds, volatility is not unrewarding to the investor. While today's VIX levels may be historically low, markets are inherently volatile. There is no reason to believe that such volatility will not resume sooner or later. Further, there is considerable body of academic evidence that any investment strategy attempting to forecast short-term

price movements is unlikely to be successful for accumulating wealth, much less reducing risk. Forecasting short-term stock market performance based on current volatility rather than prices is no different—such as currently popular low volatility fund strategies that we mentioned. Our study suggests that asset allocations corresponding with clearly defined investment objectives as well as personal risk preferences, rebalanced periodically for consistent risk exposure, and staying disciplined during periods of high volatility, are more likely to achieve positive wealth management outcomes, particularly with lower associated costs.

Smart Diversification for Targeting Premiums

Multifactor diversification based on dimensions of returns may be a smarter approach for investment management than most of the newer "smart-beta" strategies. While it is popularly believed volatility reduction is the primary benefit of diversification within stock portfolios, that is not the case. In fact, smart diversification can provide many additional investment management benefits, most particularly playing an important role in delivering better outcomes for long-term strategies, "smart-beta" or not, by capturing the full returns of targeted asset classes.

Professional Financial principally employs Dimensional Fund Advisors to design portfolio strategies that pursue higher expected returns by targeting the core factor premiums identified by financial science. For example, the Dimensional U.S. Adjusted Large Cap Equity Index, developed for research purposes by Dimensional Fund Advisors, targets the securities of the largest 1,000 companies in the U.S. market with an emphasis on the small cap, value, and

Exhibit 6: US MARKET AVERAGE MONTHLY RETURNS VS. T-BILLS, *JANUARY 1927–APRIL 2016*
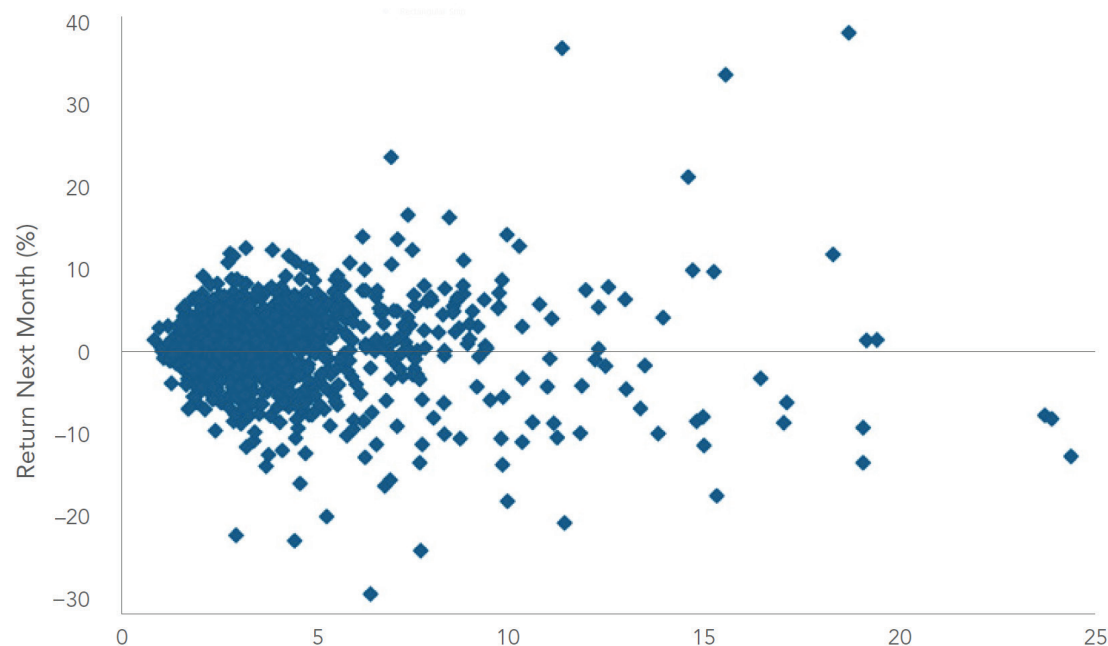
US Equity Market is the Fama/French US Total Market Index, the value-weighted return of all US CRSP firms. Data provided by Fama/French. This corresponds with data summarized in Exhibit 3.

profitability premiums.[7] Compared to the conventional Russell 1000 Index commonly used by popular index funds, a tilting toward those multifactor premiums led to an outperformance of 88 basis points per annum (12.64% vs. 11.76%) from 1979 to 2015. The average return difference is statistically reliable (with a t-stat of 3.78) as shown in **Exhibit 7.** A t-stat at a 3.29 level has 99.9% confidence.

How confident for planning strategies should we be that this Dimensional out-performance of a conventional Russell benchmark will repeat over a meaningful time horizon? **Exhibit 8** provides estimates of the probability for outperformance over differing investing horizons. As

estimated by bootstrapping (i.e., sampling with replacement) historical annual returns, these probabilities increase from 75% for a one year time frame to 92% for 10 years.[8]

Not all securities contribute equally to returns when one or more dimensional factor premiums are positive.[9] Some securities contribute greatly due to high performance, while most will have modest or poor returns. It is not possible to consistently predict which securities will have a positive realized premium and do well because in many cases, the new information about why those shares will do well prospectively either has not yet arrived or occurred.

Exhibit 7: SUMMARY STATISTICS OF DIMENSIONAL AND RUSSELL US LARGE CAP INDEXES, *JULY 1979–JUNE 2015*

	Annualized Return	Annualized Standard Deviation	Average Monthly Return	t-Stat of Return Difference	Monthly Tracking Error
Dimensional US Adjusted Large Cap Equity Index	12.64%	15.24%	1.10%	3.78	0.36%
Russell 1000 Index	11.76%	15.28%	1.03%	—	—

Past performance is no guarantee of future results. It is not possible to invest directly in an index. Please see Appendix for more information and a description of the Dimensional US Adjusted Large Cap Equity Index. The Russell 1000 Index, a conventional US large cap equity index originating in 1979, is used for comparison. Frank Russell Company is the source and owner of the trademarks, service marks, and copyrights related to the Russell Indexes.

Exhibit 8: ESTIMATED PROBABILITY OF OUTPERFORMING OVER DIFFERENT TIME HORIZONS
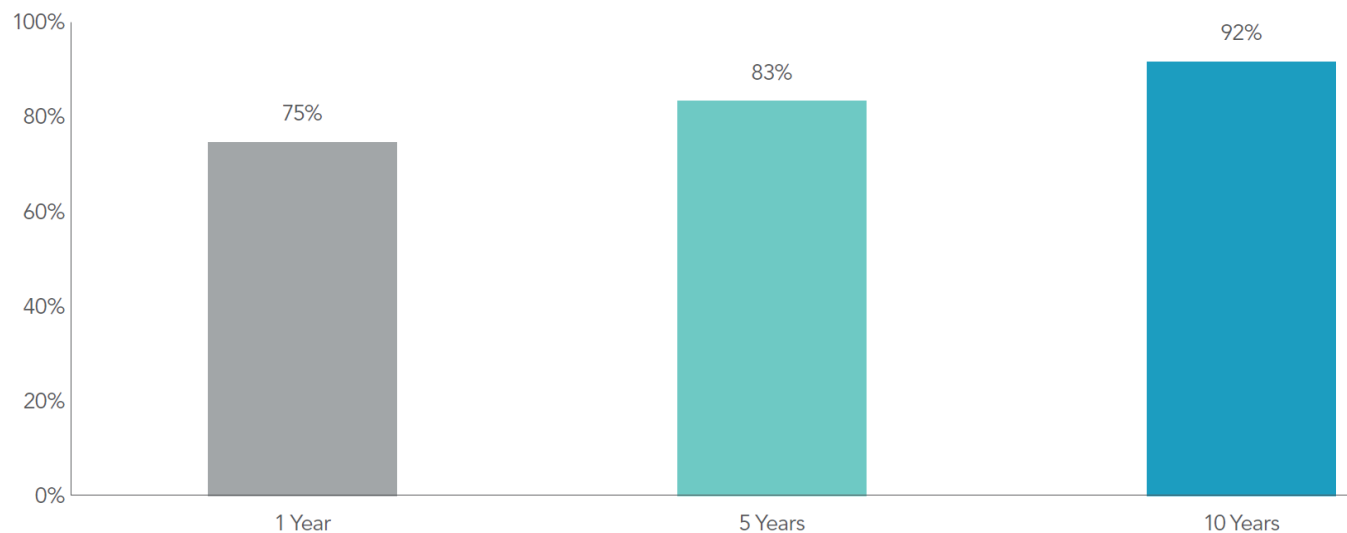
The probabilities are estimated by bootstrapping historical annual returns from July 1979 to June 2015. A bootstrap simulation is a method of analysis that can be used to approximate the probability of certain outcomes by running multiple trial runs, called bootstrapped samples, using historical returns. The projections or other information generated by bootstrapped samples regarding the likelihood of various investment outcomes are hypothetical in nature, do not reflect actual investment results, and are not guarantees of future results. Results will vary with each use and over time.

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For that reason, Professional Financial follows Dimensional holding that the most reliable way to capture the higher expected returns of equities associated with multifactor premiums is to design highly diversified portfolios of ALL stocks with continuous tilt toward size, relative price and profitability dimensional factors—all expected to deliver higher returns. Individual selection bias is avoided. A strategy that is not sufficiently diversified may inadvertently exclude holding the very companies that could generate the premium that year for the market or its dimensions.

While realizing dimensional factor premiums relative to market returns for a particular year or a series of years as in the past decade is not guaranteed, **Exhibit 8** clearly illustrates how continuously maintaining highly diversified portfolio tilts can capture multifactor returns over increasing time horizons. Moving from one year to ten years positively impacts the probability of realizing substantial outperformance from dimensional factor premiums. No Dimensional portfolio will outperform every year. But we can be confident that over reasonable horizons they can be reliably expected to do so, but not every year. Diversification always works, even when you don't want it to.

How Does Diversification Improve Expectations?

To answer this question, five multifactor equity portfolios were simulated with low (45 names) to high (1000 names) diversification levels by bootstrapping stocks from the U.S. large cap universe[10] —the greater the number of draws, the more diversified the resulting portfolios are in terms of the average number of unique names. All simulated portfolios maintain tilts toward small cap, value, and profitability premiums similar to the Dimensional U.S. Adjusted Large Cap Equity Index we discussed back in Exhibit 7. Performance of the resulting portfolios once again is measured against the conventional Russell 1000 Index. The purpose of a bootstrapping methodology is to allow disentangling the effects of diversification from other factors that might drive investment outcomes.[11]

Exhibit 9 summarizes estimates of the probability, based on number of holdings, of simulated multifactor large cap portfolios generating a higher annualized compound return than the Russell 1000 Index. The probabilities for the Dimensional U.S. Adjusted Large Cap Equity Index from Exhibit 8 are included for reference. While these portfolios attempt to beat the Russell benchmark by targeting

Exhibit 9: ESTIMATING PROBABILITY OF OUTPERFORMING US RUSSELL 1000 INDEX OVER VARIOUS TIME HORIZONS
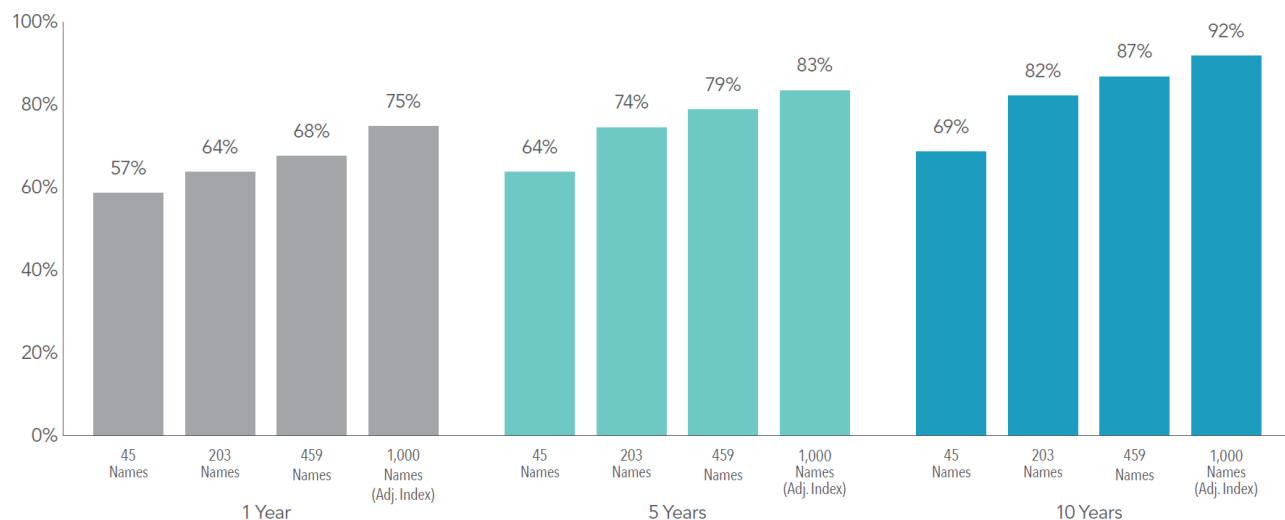
The portfolios with different diversification levels are formed by bootstrapping stocks from the large cap universe—the greater the number of draws, the more diversified the resulting portfolios are in terms of the average number of unique names. The diversification levels shown, roughly 45, 203, and 459 names on average, correspond to 50, 300, and 1000 draws, respectively. All simulated portfolios maintain the same tilts toward the small cap, value and profitability premiums as the Dimensional US Adjusted Large Cap Equity Index, and prerformance is measured by their annualized compound returns relative to the Russell 1000 benchmark. The projections or other information generated by bootstrapped samples regarding the likelihood of various investment outcomes are hypothetical in nature, do not reflect actual investment results, and are not guarantees of future results. Results will vary with each use and over time.

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multifactor premiums, the simulated portfolios' estimated probability of outperformance varies substantially depending on the number of stocks in portfolios otherwise considered diversified by industry standards. *For all time horizons, the probability of outperformance increases as portfolios are more diversified by number of names.* Exhibit 9 estimates over one year that a multifactor portfolio of about 45 names has a 57% probability of outperformance. The probability over one year increases to 68% holding about 460 names. The probability of outperformance increases significantly as time horizons expand: at 10 years, moving from 45 names to 460 names, the likely outperformance of a simulated multifactor large cap portfolio increases from 69% to 87%.

The results suggest that a multifactor strategy should be as broadly diversified as possible to increase the odds of capturing dimensional factor premiums when they occur, since the timing of their occurrence is randomly driven by news or chance events unknowable in advance. Indeed, in this case study, the highest probability of outperformance is achieved by the Dimensional U.S. Adjusted Large Cap Equity Index, which holds multifactor investments across the total eligible U. S. stock universe of the portfolio

strategy. There are other advantages to be gained by having a broad exposure across an entire market of securities, such as reducing unnecessary turnover and lowering transaction costs through flexible and patient trading, all of which may contribute incremental benefits including enhanced investment outcomes.

How does the extensive diversification of Dimensional simulated strategies compare to levels of diversification typical among U.S. mutual funds? In **Exhibit 10**, U.S. large cap core equity mutual funds are grouped by their number of holdings. Notably the vast majority of these funds are far less diversified than the 1000+ in the Dimensional U.S. Adjusted Large Cap Equity Index. The coverage at the 90th percentile is still less than 40% of the index. Even the 203 name simulated index strategy in Exhibit 9 is more diversified than over 75% of U.S. large cap equity funds routinely purchased by investors. hThese results suggest why extremely broad "smart" diversification is essential, especially when pursuing multifactor premiums. By the same token, performance reliability is unnecessarily sacrificed by the typical actively managed mutual funds and ETFs due to a lack of smart diversification. This study explains why most otherwise highly talented active fund
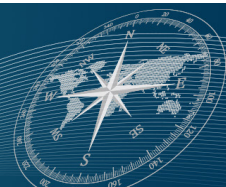
Exhibit 10: PERCENTILE HOLDINGS OF 339 US LARGE CAP EQUITY FUNDS
AS OF JUNE 2015

Percentiles	10th	25th	50th	75th	90th
Number of Holdings	35	55	90	180	394

Data source: CRSP Survivor-Bias-Free US Mutual Fund Database.

managers underperform the conventional benchmarks—similar bad luck from making selective bets and missing better investment opportunities relative to their selections.

A Higher Standard of Research

Beginning in the 1970s financial economists as well as numerous industry researchers have identified many "factors" that appear to statistically "explain" differences from regressions of equity returns. Many findings are fads, failing to hold up to close scrutiny over time. Because academic researchers and industry analysts can readily access vast troves of data from sources like Morningstar or Bloomberg, odds are exponential that "statistical flukes without theoretical support" underlie many if not most of the "factor" discoveries, according to Marcos Lopez de Prado.[12] He observes that "most back tests and time series analyzes published in journals are flawed. The problem is well-known to professional organizations. . ." and yet retraction rates are low. Especially in the hyper-competitive financial industry, endlessly searching for the next selling "edge"—such as "smart-beta" strategies in general and low-volatility funds in particular—where reputations and careers are at risk, integrity becomes commoditized.

Campbell Harvey, a professor at Duke University and president of the American Finance Association, estimates that at least half of all "discoveries" in investment research are false positives.[13] Because a virtually unlimited number of possibilities can be tested, researchers may find positive factor correlations as the result of luck alone—and may fool themselves into believing that luck didn't determine the finding. Highly statistically significant correlation does not mean causation. Brian Nosek is a psychology professor who has spent much of the last decade analyzing why so many studies fail independent testing of the same data. His theory is that because researchers have strong reputational or career incentives to come up with

"positive and clean and novel" results, they simply run regression tests for dozens of ideas, discarding those that don't confirm a statistical relationship focusing time and effort on those that do. We need "economists in particular to stop hypothesizing after results are known. . . because otherwise they cherry-pick the results they find to confirm hypotheses they never previously had."[14]

What criteria should be applied to empirical research? In academia, results that support a hypothesis make it into academic papers, while conflicting conclusions are often ignored. Intense competition for tenure or honors in that publish-or-perish environment can tempt researchers to overstate results. Across the financial industry without peer review standards, studies supporting "smart beta" low-volatility funds are based on relatively short time series are most likely contaminated by a chance relationship or the analyst's confirmation bias. Most of the data series that are available on Morningstar are simply too short or flawed for confidently making true economic inferences.

The pervasive conflicts of interest that impact peer-reviewed academic level research (let alone financial industry research) means that Dimensional Fund Advisors must work rigorously to validate research findings before theory is applied to practice with real money in real time. Dimensional must be truly confident that research findings can be reliably applied to benefit client portfolios after taking into account multiple market premiums, market frictions, and costs common to trading. Dimensional holds empirical research to a much higher standard not only than the financial services industry, but higher than any of the popular financial information firms supporting that industry.

To be considered a dimension of returns eligible for inclusion within Dimensional strategies, a premium must be:

1. Sensible
2. Persistent across time periods
3. Pervasive across markets
4. Robust to alternative specifications
5. Cost-effective to capture in diversified portfolios

This is the rationale for requiring a premium to be sensible, persistent, pervasive, and robust before it can be considered a "dimension" of expected return: "Sensible" means connecting financial theory to market data in a logical manner. Assuring empirical research is well grounded in financial economic theory is a critical safeguard against spurious correlations. Dimensional further expects premiums to be verifiable using extensive market data, and is especially vigilant against the danger of data-mining when looking at patterns of returns. Replicating results across many different sample periods, regions, and variable specifications reduces possible confirmation bias.[15]

The final hurdle before recognizing a factor as a "dimension" of expected return is the tradeoff among other premiums. Premiums interact with one another, and the marginal benefit for adding new sources of higher expected returns are diminishing. A premium might appear large when studied in isolation, but due to interaction effects, it might have a much smaller impact when examined in combination with other established premiums. For example, you cannot simply add size and relative price (value) premiums together to calculate the premium for a small value portfolio. When designing portfolios these interactions must be accounted for. A parsimonious set of dimensions can explain the vast majority of differences in expected returns. A premium must improve expected returns after accounting for premium interactions and the practical costs related to obtaining that premium in a portfolio.[16]

Conclusion for Inclusion

Decades of academic-grade research guide Dimensional's exacting methodology for putting financial science to work. In equities, only three dimensions of expected return for the market meet demanding standards: *company size* (small cap/large cap), *relative price* (high/low value), and recently *direct profitability* (high/low). Two dimensions cover fixed income: *term* (maturity) and *credit spread*

(quality). These underlying factors are supported by economic valuation theory for dimensionality of expected returns.[17] These factors appear everywhere Dimensional looks—in different time periods and in markets worldwide. Finally, they can be captured with reasonable levels of trading.
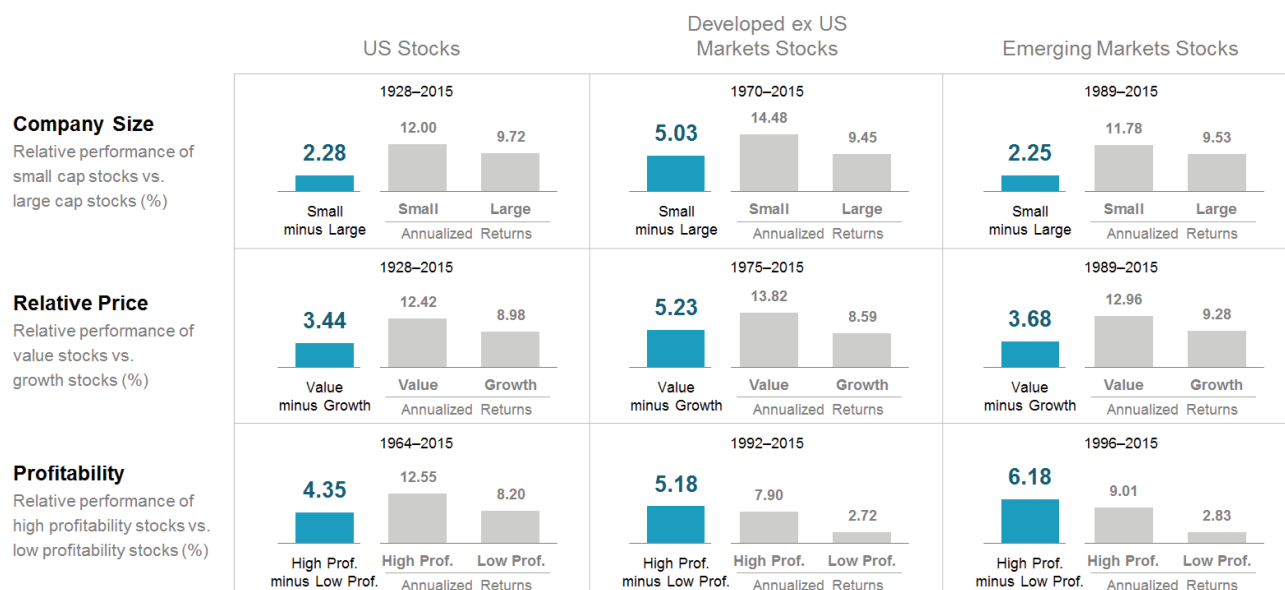
Because empirical research is always uncertain—we have only one set of historical market data, and controlled economic experiments are rarely possible—Dimensional exercises a great deal of caution when conducting, interpreting, and applying empirical studies. While history may echo, it does not repeat. Dimensional's thorough research standards reduce the risk of misinformed regressions, but the possibility that multifactor premiums may not reappear always exists. This is why Professional Financial structures well-diversified, low-turnover, tax-efficient portfolios that are sensible strategies even if some targeted premiums may not be realized for years.

Theoretical and empirical research in finance over the past 60 years has enormously advanced our knowledge of
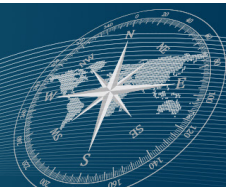
Exhibit 12: DIMENSIONS OF EXPECTED RETURNS

Historical premiums and returns (annualized): US, Developed ex-US, and Emerging Markets

	US Stocks	Developed ex US Markets Stocks	Emerging Markets Stocks
Company Size — Relative performance of small cap stocks vs. large cap stocks (%)	1928–2015 — Small minus Large: 2.28; Small: 12.00, Large: 9.72 (Annualized Returns)	1970–2015 — Small minus Large: 5.03; Small: 14.48, Large: 9.45 (Annualized Returns)	1989–2015 — Small minus Large: 2.25; Small: 11.78, Large: 9.53 (Annualized Returns)
Relative Price — Relative performance of value stocks vs. growth stocks (%)	1928–2015 — Value minus Growth: 3.44; Value: 12.42, Growth: 8.98 (Annualized Returns)	1975–2015 — Value minus Growth: 5.23; Value: 13.82, Growth: 8.59 (Annualized Returns)	1989–2015 — Value minus Growth: 3.68; Value: 12.96, Growth: 9.28 (Annualized Returns)
Profitability — Relative performance of high profitability stocks vs. low profitability stocks (%)	1964–2015 — High Prof. minus Low Prof.: 4.35; High Prof.: 12.55, Low Prof.: 8.20 (Annualized Returns)	1992–2015 — High Prof. minus Low Prof.: 5.18; High Prof.: 7.90, Low Prof.: 2.72 (Annualized Returns)	1996–2015 — High Prof. minus Low Prof.: 6.18; High Prof.: 9.01, Low Prof.: 2.83 (Annualized Returns)

Information provided by Dimensional Fund Advisors LP. The S&P data is provided by Standard and Poor's Index Services Group. MSCI data © MSCI 2016, all rights reserved. In USD.

US size premium: Dimensional US Small Cap Index minus S&P 500 Index. US relative price premium: Fama/French US Value Index minus Fama/French US Growth Index. US profitability premium: Dimensional US High Profitability Index minus Dimensional US Low Profitability Index. Dev. ex US size premium: Dimensional Intl. Small Cap Index minus MSCI World ex USA Index (gross div.). Dev. ex US relative price premium: Fama/French Intl. Value Index minus Fama/French Intl. Growth Index. Dev. ex US profitability premium: Dimensional Intl. High Profitability Index minus Dimensional Intl. Low Profitability Index. Emerging Markets size premium: Dimensional Emerging Markets Small Cap Index minus MSCI Emerging Markets Index (gross div.). Emerging Markets relative price premium: Fama/French Emerging Markets Value Index minus Fama/French Emerging Markets Growth Index. Emerging Markets profitability premium: Dimensional Emerging Markets High Profitability Index minus Dimensional Emerging Markets Low Profitability Index. Profitability is measured as operating income before depreciation and amortization minus interest expense scaled by book.

financial markets. That several multifactor variables can identify securities with higher expected returns in equity markets is well documented. The findings of this huge body of research are not secret and are well known to the financial industry. Dimensional is deliberate both in how they interpret data and how they employ data for portfolio construction. Dimensional carefully builds portfolios that consider tradeoffs among premiums and seeks multiple opportunities to add value. Their portfolios are robust— they seek to deliver consistent results under a wide variety of market conditions and specifications. No "smart-beta" funds adhere to such rigorous standards.

Realizing dimensional premiums may require years of commitment to an investment policy strategy. Still, Dimensional portfolios are excellent solutions even without the factors re-appearing. But by targeting multiple dimensions of expected return, Professional Financial gives clients more peace of mind that they can meet their family's planning challenges with more confidence than with any of the "smart beta" vehicles popularly marketed.

Our takeaway regarding the so-called "smart-beta" strategies is simple: while recent performance of certain funds may have had attractive recent returns, past performance is no guarantee of future results. Smart-beta funds lack the evidence-based research standards Professional Financial requires for planning wealth preservation. While our paper focused on diversification of stocks within an asset class, in practice, investment management should diversify worldwide across industries, sectors and countries. By structuring portfolios weighed by global market capitalization while maintaining a consistent tilt toward dimensional factors, we improve the reliability of planning outcomes to more confidently achieve the hopes and dreams of those who entrust us with their wealth.

1   Market Attributes: Risk & Volatility Index Dashboard (S&P Dow Jones Indices), July 2016

2   Brian Hershberg, *Wealth Advisor Daily Briefing* (July 21, 2016).

3   Joe Carlson, director of global economic research at AllianceBernstein LP from Rich Miller, "Wealth Bubble Sending Scary Signal About Future U.S. Downturn," Wealth Management.com (July 22, 2016)

4   See for instance, Haugen, Robert A. & Narden L. Baker, "The efficient market inefficiency of capitalization-weighted stock portfolios," *Journal of Portfolio Management* (Spring 1991): 35-40.

5   *Global Equity Markets: June 2016*, Dimensional Fund Advisors. Value 30% for lowest B/M, growth 30% for highest B/M sort.

6   Eugene F. Fama & Kenneth R. French, "Q&A: Timing Volatility," Fama/French Forum, December 19, 2008, www.dimensional.com/famafrench/questions-answers/qu-timing-volatility.aspx.

7   Dimensional US Adjusted Large Cap Equity Index: January 1975–present: Compiled by Dimensional from CRSP and Compustat data. Targets shares of the largest 1,000 US companies traded on NYSE, NYSE MKT (formerly AMEX), and Nasdaq Global Market with an emphasis on companies with smaller capitalization, lower relative price, and higher profitability. Exclusions: non-US companies, REITs, UITs, and investment companies. The index has been retroactively calculated by Dimensional and did not exist prior to December 2012. The calculation methodology for the Dimensional US Adjusted Market 1 Index was amended in January 2014 to include direct profitability as a factor in selecting securities for inclusion in the index.
    June 1927–December 1974: Targets the securities of the largest 1,000 US companies traded on the NYSE, NYSE MKT (formerly AMEX), and Nasdaq Global Market with an emphasis on companies with smaller capitalization and lower relative price.

8   Computations for this and next section by Wei Dai, "Research Matters: How Diversification Impacts the Reliability of Outcomes," Dimensional Fund Advisor white paper (June 2016)

9   For example, Fama and French, consultants for Dimensional Fund Advisors, documented how different transition groups have contributed to the small cap and value premiums as stocks transitioned across different size and relative price portfolios. Source: Fama, Eugene F. & Kenneth R. French, "Migration," *Financial Analysts Journal* 63, No. 3 (May-June 2007): 48-58.

10 The US large cap equity universe is defined as the top 1,000 names by market capitalization in the US stock market. Data sources: CRSP and Compustat data for US firms listed on the NYSE, AMEX, or NASDAQ.

11 See appendix for methodology of bootstrapping return series.

12 Lopez de Prado, Marcos, "The Future of Empirical Finance," *Journal of Portfolio Management* 41 No. 4 (2015). SSRN: http://ssm.com/abstract=2609734.

13 Harvey, Campbell R. & Yan Liu, "Evaluating Trading Strategies," *Journal of Portfolio Management* 40, No. 5 (2014): 109-118.

14   Nosek, Brian, "HARKing Back: Lesson in Investing from Science," The Psy-Fi Blog (Feb 1, 2016) http://www.psyfitec.com/2016/02/harking-back-lessons-in-investing-from.html

15   The original multifactor research of Fama and French published in 1991 was based on evidence of U.S. stocks from 1963 to 1990. The results were questioned, and required out-of-sample tests. First, data was collected from 1926 to 1962 and examined. Second, independent data on the performance of stocks in developed countries and emerging markets around the world were collected and examined. Factor sensitivities were statistically consistent with original patterns observed in U.S. stocks. Further, recent data that continues to be collected confirms the original factor observations.

16   Morningstar is introducing its own "Global Risk Model" based on 36 "factors" which include styles, sectors, regions and currencies. In addition to dimensions, they include volatility, momentum, liquidity, "economic moat," "fair value," "valuation uncertainty," and "financial health." While this list is likely exhaustive for measurable economic risks, it appear most useful for for the services Morningstar sell. The model's baseline goes back only to 2002, in the aftermath of the tech bust's worst year.

17 Fama, Eugene F. & Kenneth R. French, "Profitability, Investment, and Average Returns," *Journal of Financial Economics* 82, No. 3 (2006): 491-518.

Appendix: Methodology

We simulate US large cap portfolios with different diversification levels and over different investment horizons, while maintaining the same level of tilt toward small cap, value, and profitability premiums as the Dimensional US Adjusted Large Cap Equity Index. The simulations take two steps for a given investment horizon of N years and number of draws n:

■ Bootstrap N times from the years in the sample period (1979-2015).

■ For each year drawn in the first step, bootstrap n stocks from the US large cap universe into the portfolio. The US large cap universe is defined as the top 1,000 names by market capitalization in each year. The sampling probabilities are proportional to stocks' tilted market cap weights, which reflect an increased focus on the small cap, value, and profitability premiums.

For each simulation, we calculate the annualized compound return difference between the simulated portfolio and the large cap benchmark (Russell 1000 Index). We repeat the simulation 50,000 times to obtain a distribution of the return differences and calculate the percentage of positive return differences (i.e., when simulated portfolios outperform the benchmark) across simulations. The projections or other information generated by bootstrapped samples regarding the likelihood of various investment outcomes are hypothetical in nature, do not reflect actual investment results, and are not guarantees of future results. Results will vary with each use and over time.