OutDex™ to Outperform an Index: *Incorporating the Best of Active and Passive Investment Strategies*

Edward N.W. Aw, Christopher R. Dornick, John Q. Jiang, and Gregory Y. Sivin

Edward N.W. Aw
is head of quantitative strategies at Bessemer Investment Management LLC in New York, NY.
aw@bessemer.com

Christopher R. Dornick
is a quantitative analyst at Bessemer Investment Management LLC in New York, NY.
dornick@bessemer.com

John Q. Jiang
is a senior quantitative analyst at Bessemer Investment Management LLC in New York, NY.
jiang@bessemer.com

Gregory Y. Sivin
is a senior quantitative analyst at Bessemer Investment Management LLC in New York, NY.
sivin@bessemer.com

There are two general approaches to investment management: utilizing either active investment management or passive investment management. An active investment managers' goal is to outperform a specific benchmark index by identifying mispriced securities. A passive managers' goal is to closely track or replicate the return pattern of a specified benchmark index at a low cost. A passive manager does not make any attempt to seek out mispriced securities.

The active versus passive investment debate has been ongoing since the mid-1970s, with the introduction of index funds. The first index fund for individual investors was the First Index Investment Trust sponsored by the Vanguard Group. The initial public offering was completed on August 31, 1976. Although the arguments for active or passive investing have been covered by academia and practitioners alike ad nauseam, the debate continues as a result of the dialogue about mispriced securities.

At any given moment, security prices represent the best estimate of fair value by all market participants. A particular security may have a better outlook owing to its competitive position, superior technology, product recognition, financial strength, and so on. Differences in that outlook by market participants create mispricing. Sharpe [1991] argued that the average active manager should be expected to underperform the average passive manager by the cost of managing the active fund. Sharpe's premise centered on the concept of a zero-sum game: At any given moment, the holdings of all investors form the aggregate market, and the value of one investor's outperformance of the aggregate market must be accompanied by a similarly valued underperformance. As such, the average actively managed dollar will equal that of the passively managed dollar, before costs.

Although Sharpe's 1991 work has been cited to support the attractiveness of a passive investment strategy, it is premature to conclude that active investment does not deliver value. Sharpe's study relates to the average actively invested dollar or the average performance of active management. An argument can be made that an above-average or skilled active investment manager can theoretically deliver returns above the benchmark index. However, skill may not be enough, as argued by Grinold [1989] when he introduced the fundamental law of active management. The fundamental law of active management states that the information ratio (IR) is a function of the manager's skill (information coefficient [IC]) and the number of times the manager uses that skill.[1] IR measures how much excess return an active manager can generate relative to the amount of tracking risk taken versus a benchmark index.

It would seem that the debate over active versus passive investment is a function of not just a manager's skill, but also how often that skill is applied. Using baseball as an analogy, let us compare a Hall of Fame player with a 0.350 lifetime batting average to an average player with a 0.250 lifetime batting average. In any given game during a season, a Hall of Fame player may get zero hits in four at bats, whereas the average player may go four for four. With this small sample size, it would seem the Hall of Fame player does not have much skill. However, over a week, a month, a season, and a career, one would expect the skill of the Hall of Fame player to shine as the sample size increases.

In practice, the performance delivered by active managers does little to settle the debate. Soe [2015] showed that, over the most recent five-year period, the majority of active managers failed to outperform their respective benchmark index based on net-of-fee returns. Bogle [1992], the founder of the Vanguard Group, maintained that passive investing wins the debate and that most managers cannot consistently beat the benchmark index after adjusting for costs.

Despite the poor performance delivered by the majority of active managers, the debate persists today because there are indeed active investment managers who beat the benchmark index. Aw et al. [2014] proposed a disciplined investment process that combines quantitative and fundamental analyses—a quantamental approach. The authors provided evidence that a systematic security selection process to identify mispriced securities, driven by a rigorously tested quantitative model and created to harmoniously support talented fundamental analysts, should lead to strong long-term investment performance.

The preference for a passive or active investment strategy would then depend on the type of investor, the investment objectives, and the investment time horizon. A skilled investor who can successfully and consistently identify mispriced securities may prefer an active investment strategy. A novice investor or an investor with limited resources who is less able to identify mispriced securities may prefer a passive strategy that will reasonably track the performance of a benchmark index.

Historically, passive investing is synonymous with using a mutual fund or exchange-traded fund (ETF) in which the fund mirrors a market index. The recent rise of smart beta strategies suggests investors are moving away from traditional market capitalization–weighted indexes to alternative weighted indexes. Smart beta strategies profess to deliver a better risk return profile than traditional indexes. The weighting scheme of a smart beta strategy is based on measures such as volatility, yield, and other fundamental factors. Although the smart beta phenomenon may be recent, factor-based investing has been used by quantitative investors in the investment industry for the past 30 or more years. Basu [1977] concluded that a low price to earnings portfolio yielded superior returns on a risk-adjusted basis. Fama and French [1992] found that book to market provides insights into a cross-section of average stock returns, and Naranjo et al. [1998] found a consistent positive relationship between dividend yield and stock returns. Jones [1998] concluded that the valuation anomalies are significant and pervasive at both global and country levels.

Quantitative investors using a factor-based investing strategy recognize that employing only a single factor may result in an investment strategy that will not consistently work. Therefore, most quantitative investors would prefer a multi-factor strategy in which the benefit of combining less correlated factors is realized. A novice investor investing in a smart beta strategy that employs a value strategy must understand that the portfolio consists of securities that are cheap at the present time as based on valuation. This portfolio is therefore not diversified, unlike the traditional capitalization-weighted index, and there will be periods in which participants in the overall market will not reward cheap valuation. During such a period, the smart beta strategy based on valuation will underperform. For the novice investor, a well-diversified portfolio across available smart beta strategies is needed to achieve a better risk and reward profile.

Kang and Ung [2015] highlighted the debate surrounding factor-based portfolio construction. An asset allocation decision across smart beta strategies must be made; because tactical allocation or timing of the factors will be difficult, novice investors may find themselves continually chasing high-performing smart beta strategies only to net an inferior risk and reward profile.

Therefore, we propose an OutDex™ strategy that is designed to closely track market capitalization–weighted indexes while providing investors with factor-based excess returns. The strategy thus incorporates the best of active and passive investment. Furthermore, the OutDex™ strategy employs a quantitative approach to active investing that is scalable and less-expensive than usual active investment management.

The remainder of this article is organized as follows: the next section describes the data, with the following section discussing the research and design of an OutDex™ strategy, the next presenting empirical results, and the final section offering our conclusions.

DATA

The research universe is defined as the constituents of the S&P Global Broad Market Index and the S&P 1500 Index. To avoid survivorship bias, not only did we include companies that are currently trading, but also companies that have dropped out of our data sample as the result of a bankruptcy or a merger. Therefore, we are confident that our backtest results are unlikely to suffer from upward performance bias. Fundamental data for U.S.-domiciled securities were retrieved from Compustat Point-in-Time Quarterly databases for the period December 31, 1993 to March 31, 2015. Fundamental data for non-U.S.-domiciled securities were retrieved from the FactSet Fundamentals database for the period December 31, 1993 to March 31, 2015; these data were used with an appropriate lag to avoid look-ahead bias. Stock price/returns data were provided by FactSet Research Systems, Inc. The starting date of December 31, 1993, is due to data availability.

RESEARCH AND DESIGN

The goal in developing the OutDex™ strategy is to incorporate the best of index investing with an active investment management process. We developed a disciplined portfolio construction process to mimic the characteristics of a benchmark index while concurrently considering an active overlay process to achieve the OutDex™ strategy.

Expected Return Signal for the Active Overlay

The active overlay process is a research process that systematically organizes data and edits out market noise. A successful overlay process uses a stock screen that contains screening criteria or factors that are catalysts of stock returns. Factors can generally be grouped as fundamental, macroeconomic, technical, or stock specific. *Fundamental factors* are metrics used by fundamental research analysts, such as book to market, price to earnings, and return on invested capital, among others. *Macroeconomic factors* can be based on the arbitrage pricing theory (APT) model introduced by Chen et al. [1986] or on measures of supply and demand such as the ISM (Institute of Supply Management) Manufacturing Index. *Technical factors* are measurements often used by active traders such as price momentum, relative strength index, Bollinger bands, and so on. Jegadeesh and Titman [1993] found that buying stocks that have performed well in the past and selling stocks that have performed poorly can generate future positive returns over a time horizon of less than one year. Finally, *stock-specific factors* are attributes that are unique to individual stocks. Fundamental research analysts often search for stock-specific factors, including a company's unique position, product, or service, which can be a source of excess returns relative to the overall market. However, the high volatility of these stock-specific factors can lead to poor future performance, as found by Ang et al. [2009]. Stock screens and the validity of factors are covered extensively in academic journals as well as by Wall Street research.

For this article, we chose a well-known screening approach based on Joel Greenblatt's [2005] *New York Times* best seller, *The Little Book That Beats the Market*. The overlay strategy is to favor securities that are cheap and return capital to shareholders. Greenblatt used earnings yield defined as earnings before interest and tax (EBIT) or operating income divided by enterprise value to determine the cheapness of a security. Return on capital (ROC), defined as EBIT divided by the sum of net fixed assets plus working capital, was used to evaluate capital returns to shareholders. We defined cheapness and return to shareholders slightly differently from Greenblatt based on our factor research. We selected free cash flow to price to evaluate the cheapness of non-financial companies and book to price to evaluate the cheapness of financial companies. Return on invested capital (ROIC), defined as earnings before interest, taxes, depreciation and amortization (EBITDA) divided by average total assets, was used to evaluate return to shareholders of non-financial companies. Return on equity (ROE), defined as net income divided by average shareholders' equity, was used to evaluate return to shareholders for financial companies. We followed the same methodology presented in Aw et al. [2014] to validate the performance of the four selected factors. The Appendix explains the calculation methodology of measurement statistics of Aw et al. [2014] used in Exhibit 1.

EXHIBIT 1

Back-Test Results, Various Holding Periods

	BVA	TAV	Quintile 1 PHR	Quintile 1 *t*-Stat	Quintile 5 PHR	Quintile 5 *t*-Stat	IC
Free Cash Flow to Price							
3-Month Holdings Period	4.5	4.7	71.0	7.20	30.6	−10.93	0.06
6-Month Holdings Period	4.0	4.3	72.2	7.99	28.2	−14.58	0.08
12-Month Holding Period	3.5	3.6	80.5	8.87	23.6	−17.14	0.11
18-Month Holding Period	2.9	2.9	78.8	9.72	20.4	−18.75	0.12
24-Month Holding Period	2.6	2.6	79.1	9.37	16.7	−17.77	0.13
36-Month Holding Period	2.2	2.1	82.9	9.98	14.0	−14.95	0.14
Book to Price†							
3-Month Holdings Period	3.2	2.8	54.1	0.35	45.5	−1.81	0.03
6-Month Holdings Period	2.7	3.1	54.4	–0.01	44.0	−1.92	0.03
12-Month Holding Period	2.9	3.7	61.8	1.98	37.0	−2.49	0.05
18-Month Holding Period	2.6	3.2	65.0	3.26	31.7	−4.53	0.07
24-Month Holding Period	2.5	2.8	68.8	3.51	28.2	−6.68	0.09
36-Month Holding Period	2.0	2.3	68.0	2.26	26.1	−9.14	0.10
ROIC							
3-Month Holdings Period	3.6	5.7	67.5	6.54	29.0	−9.70	0.06
6-Month Holdings Period	3.7	5.3	72.6	9.21	23.4	−12.79	0.08
12-Month Holding Period	3.4	4.5	74.8	10.96	21.1	−15.30	0.10
18-Month Holding Period	2.9	3.4	75.4	11.18	20.0	−18.15	0.10
24-Month Holding Period	2.5	2.9	72.6	9.83	14.5	−17.35	0.11
36-Month Holding Period	2.0	2.3	65.8	9.30	7.7	−16.03	0.12
ROE†							
3-Month Holdings Period	2.1	4.4	58.8	0.45	42.4	−5.11	0.05
6-Month Holdings Period	2.0	3.6	59.1	0.59	36.9	−5.55	0.06
12-Month Holding Period	1.7	2.6	61.0	1.74	39.8	−4.80	0.07
18-Month Holding Period	1.7	2.3	59.2	1.36	40.4	−5.67	0.07
24-Month Holding Period	1.7	2.2	58.5	0.94	38.9	−5.92	0.06
36-Month Holding Period	1.5	2.0	54.1	–1.52	39.6	−9.38	0.05

Notes: BVA, TAV, & PHR in annualized percentage terms.

†*Financial companies only.*

We assigned cheap securities that return capital to their shareholders to Quintile 1, whereas securities on the opposite end of the spectrum were placed in Quintile 5.

The OutDex™ Algorithm

The goal of an OutDex™ strategy is to mimic the characteristics of a benchmark index while concurrently employing an active expected return overlay. Exhibit 2 demonstrates the OutDex™ algorithm for the S&P 500 Index.

Exhibit 2 represents the constituents of the S&P 500 Index on a (x, y) scatter plot where x is a trailing 12-month volatility based on daily returns of the securities and y is the raw expected return score using a screen comparable to Joel Greenblatt's screen, discussed earlier. The raw expected return scores are also grouped by quintiles (Quintile 1 = Most Attractive, Quintile 5 = Least Attractive). The size of the bubbles represents the weight of the security in the S&P 500 Index; the shade of the bubbles represents sectors based on sector classification. The shaded areas on the graph indicate the securities that are below and above the volatility threshold. Exhibit 3 describes the OutDex™ algorithm's weight-adjustment process.

Securities in Quintile 1 and Quintile 2 are adjusted upward, whereas securities in Quintile 4 and Quintile 5 are adjusted downward. No adjustments were made to the securities in Quintile 3, as our expected return signal for those securities is neutral. This weight adjustment by definition is active weight because our initial weight is always the underlying benchmark index weight. The amount of weight adjustment is a function of the desired tracking error (TE)[2] to the underlying benchmark index, as shown in Exhibit 4.

Alternatively, one can think of the adjustment as active share, as proposed by Cremer and Petajisto [2009].

Exhibit 2

A Visual Representation of an OutDex™ Algorithm

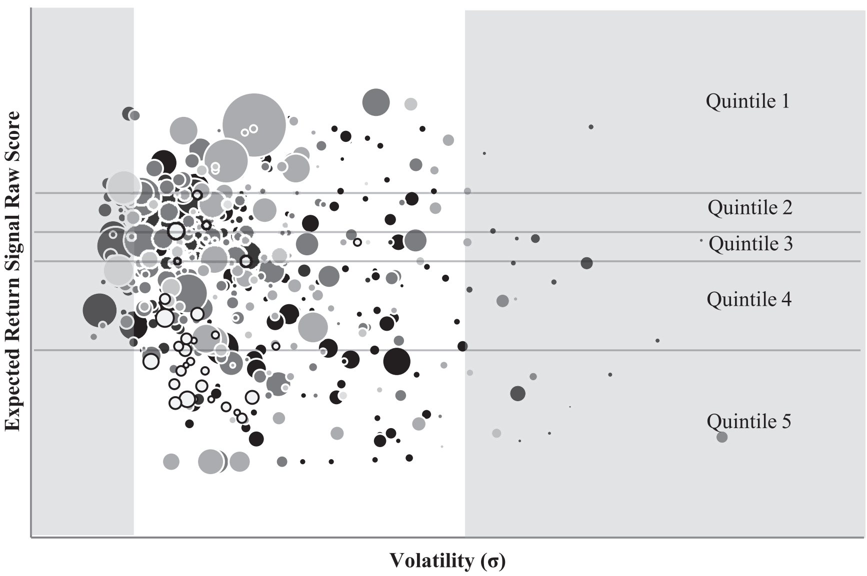
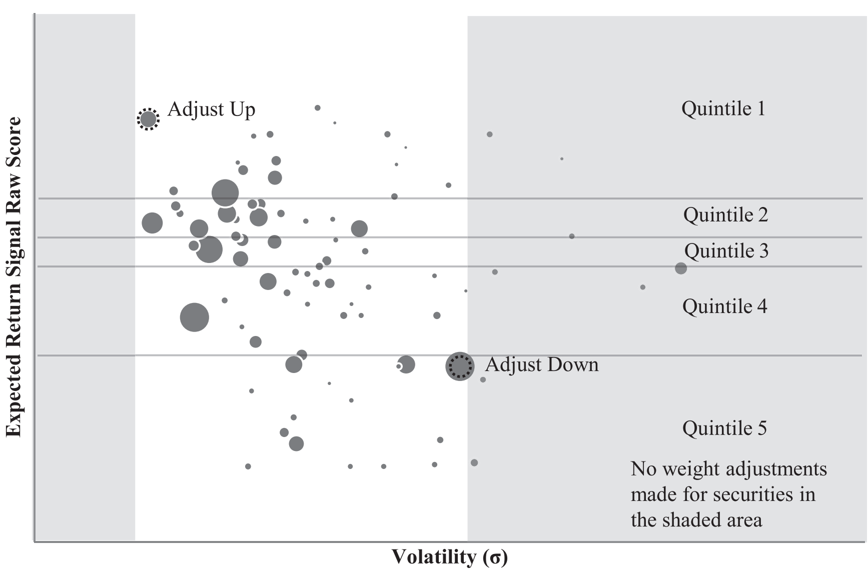


Exhibit 3

Adjusting the Weights of Constituents in Sector$_i$



As indicated in Exhibit 2, the shaded areas on the graph indicate the securities that are below and above the volatility threshold. No adjustments were made to those securities in the shaded area for two reasons: First, the securities on the high end of the volatility spectrum are too unstable for the expected return model to create a stable return expectation; second, the securities on the lower end of the volatility spectrum are not likely to significantly alter the performance of the underlying benchmark index. Exhibit 5 describes OutDex™ portfolio construction of constituents in sector$_i$.

The securities in sector$_i$ are sorted in descending adjusted-weight order. A minimum threshold weight is determined, and securities below the threshold are put aside. The minimum threshold weight is a function of the desired security count in the OutDex™ portfolio. A bin for sector$_i$ is created, with its weight capacity determined by sector$_i$'s weight in the underlying benchmark index. The securities in sector$_i$ are now placed into the bin. All securities above the threshold must be included in the bin. If capacity is reached, the weights will be reduced pro-rata to accommodate all securities above the minimum weight threshold. If the aggregate weight of the securities above the minimum weight threshold falls short of the bin, then the securities below the minimum threshold are used to resolve the shortfall:

$$W_P = \sum_i w_i \tag{1}$$

where W_P = total weight of the OutDex™ portfolio; w_i = the weight of sector$_i$; and i = total number of sectors. Lower quintile securities are given priority over higher quintile securities. The process described in Exhibit 5 will be repeated for all sectors to construct the OutDex™ portfolio.

EXHIBIT 4

Active Weight and Tracking Error

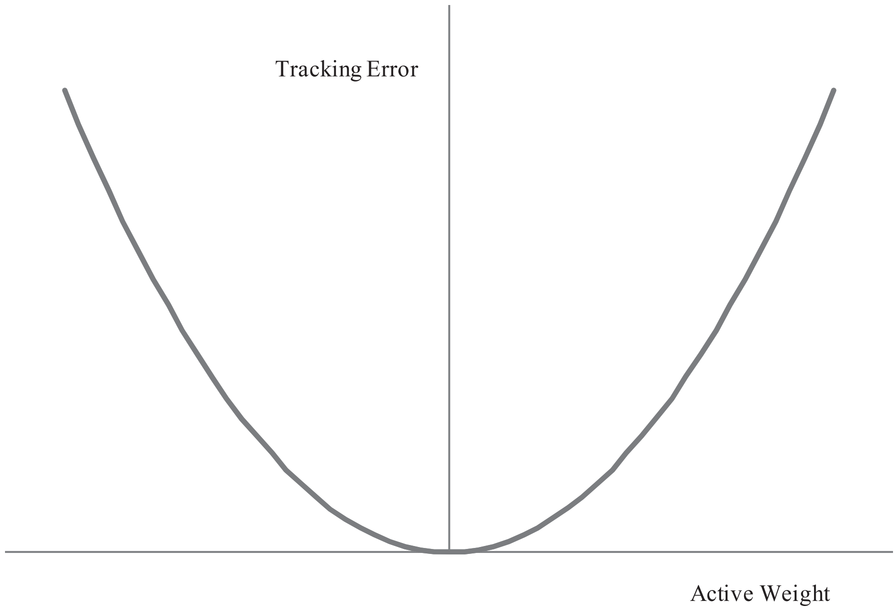
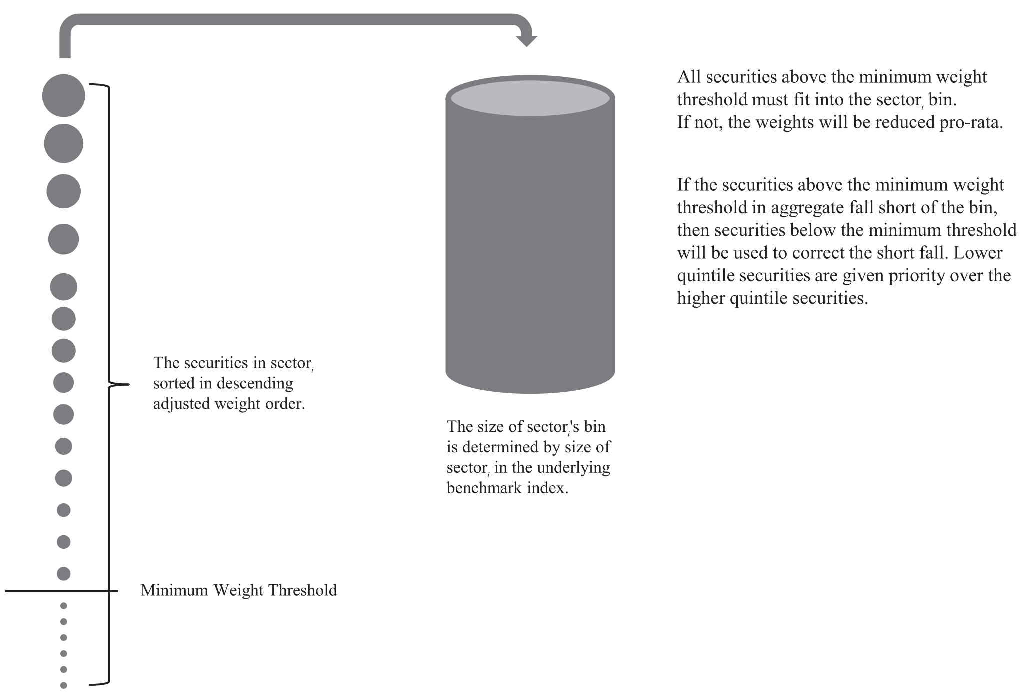


EXHIBIT 5

OutDex™ Portfolio Construction of Sector$_i$



If the underlying benchmark index is a global portfolio then the process described in Exhibit 5 is repeated for all sectors in each region of a global portfolio:

$$W_P = \sum_j \sum_i w_{R_j S_i} \qquad (2)$$

where W_P = total weight of the OutDex™ portfolio; R_j = the weight of region$_j$; j = total number of regions; S_i = the weight of sector$_i$; and i = total number of sectors.

The construction processes as described in Exhibit 2, Exhibit 3, and Exhibit 5 are performed based on a set rebalancing frequency.

RESULTS

The OutDex™ performance measurement statistics shown in Exhibit 6 for various regions, countries, and sectors provide evidence of a robust portfolio construction process that can consistently outperform a benchmark index. The *t*-Stats indicate that the excess returns from all OutDex™ portfolios are statistically significant at the 95% confidence level.

As stated in the third section of this article, the weight-adjustment amount and the minimum weight threshold level can be altered to meet the desired investment objective (e.g., a smaller weight adjustment results in an OutDex™ portfolio that tracks the underlying benchmark index more closely).

Risk and Return Decomposition

To determine the source of the excess return and tracking error presented in Exhibit 6, we conducted quarterly tracking risk and return decomposition for each of the OutDex™ portfolios. We used the Northfield Information Services global equity risk model for risk decomposition. The Northfield global equity risk model takes into account a portfolio's exposure to region, sector, interest rates, oil prices, currency, value/growth style, market development, company size, and the five

EXHIBIT 6

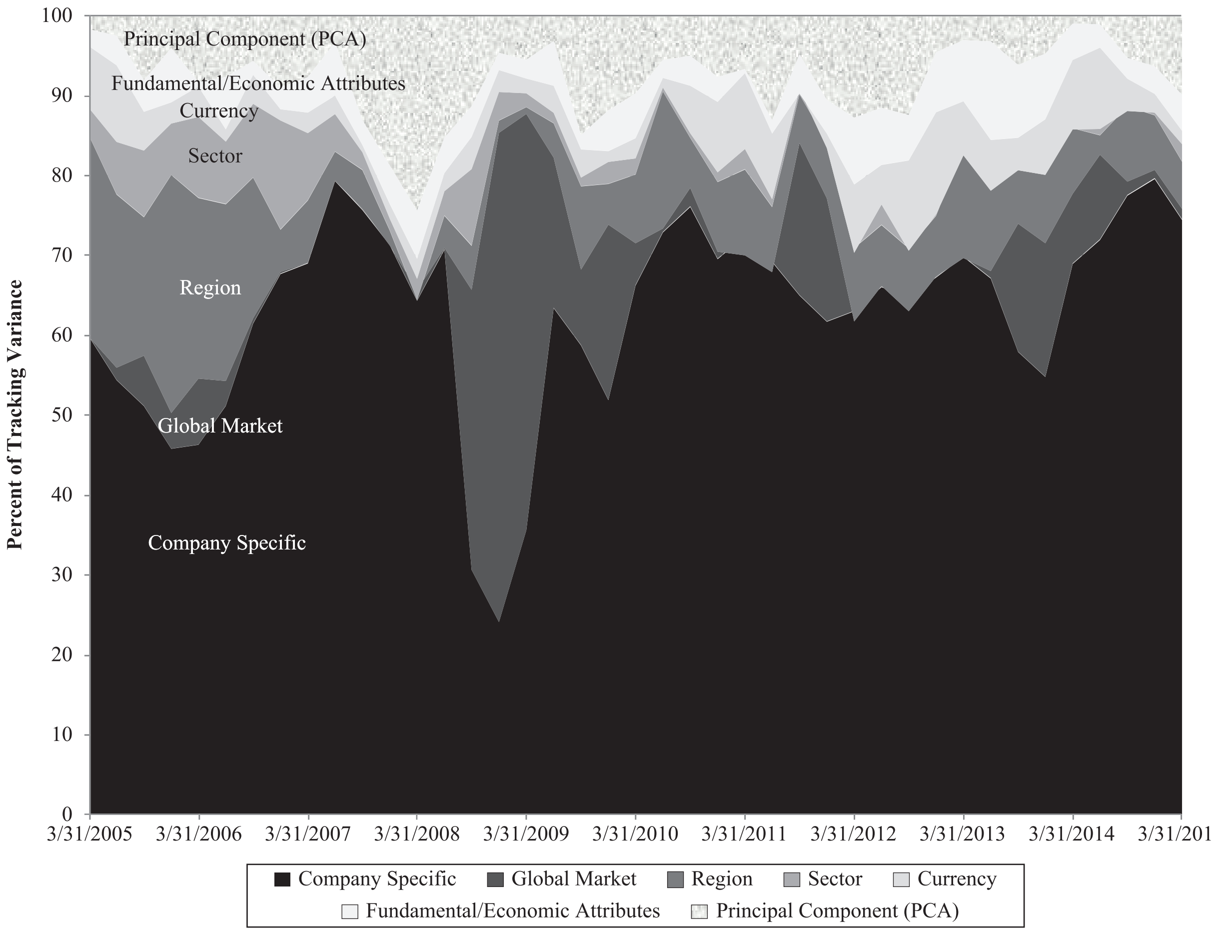
OutDex™ Performance History as of March 31, 2015

	Annual Return (%)				Annual Volatility (%)			Statistics				
	OutDex	Index	Excess	Excess *t*-Stats	OutDex	Index	Excess	Hit Rate (%)	TE	Beta	Correl	T/O (%)
Region												
Dev. Europe LargeMid*	8.89	8.16	0.73	3.17	17.6	17.7	–0.13	60.8	0.95	0.99	1.00	33
Dev. Europe Small*	12.76	9.71	3.05	7.19	18.5	18.7	–0.27	72.2	1.73	0.98	1.00	56
Global LargeMid*	9.96	7.89	2.07	6.18	15.4	15.4	–0.03	65.5	1.42	0.99	1.00	53
Global MidSmall*	14.23	9.16	5.07	6.09	16.2	17.1	–0.91	67.5	3.26	0.93	0.98	113
Emerging Market***	10.61	7.44	3.17	6.64	22.5	22.8	–0.22	72.1	1.69	0.99	1.00	47
Country												
U.S. Large*	10.48	9.36	1.12	4.20	14.7	14.9	–0.22	62.4	1.09	0.98	1.00	39
U.S. Mid*	13.37	12.14	1.24	3.29	17.0	17.2	–0.24	58.8	1.49	0.98	1.00	33
U.S. Small**	13.44	11.69	1.75	4.46	18.3	18.8	–0.45	58.8	1.50	0.97	1.00	63
Japan LargeMid*	2.02	1.31	0.71	1.93	18.4	18.6	–0.25	54.9	1.55	0.98	1.00	12
Japan MidSmall****	10.45	8.79	1.67	2.74	12.7	12.9	–0.16	59.4	1.33	0.98	0.99	52
Japan Small*	2.38	1.62	0.76	1.68	19.1	19.0	0.08	57.3	2.09	1.00	0.99	60
Sector												
Global Energy*	10.59	9.78	0.81	2.10	20.5	20.0	0.49	54.5	1.84	1.02	1.00	18
Global Materials*	8.48	7.17	1.31	5.23	20.5	20.7	–0.23	62.7	1.03	0.99	1.00	28
Global Industrials*	9.71	7.66	2.05	4.63	16.8	17.1	–0.30	61.6	1.84	0.98	0.99	36
Global Consumer Discretionary*	9.89	7.81	2.08	5.25	16.5	17.0	–0.49	60.0	1.61	0.97	1.00	44
Global Consumer Staples*	11.73	10.65	1.07	5.53	11.7	11.8	–0.13	62.4	0.80	0.99	1.00	25
Global Health Care*	14.51	12.28	2.23	6.03	12.7	12.8	–0.12	68.2	1.50	0.98	0.99	25
Global Financials*	8.83	6.65	2.18	5.07	19.1	18.9	0.13	62.4	1.87	1.00	1.00	37
Global Information Technology*	11.02	9.36	1.65	3.71	24.6	25.4	–0.79	61.6	1.61	0.97	1.00	24
Global Telecom Services*	7.92	7.13	0.79	2.13	18.8	18.7	0.12	56.5	1.62	1.00	1.00	18
Global Utilities*	8.02	7.19	0.83	3.87	12.4	12.7	–0.25	58.8	0.89	0.98	1.00	24

**Start Date: 12/31/1993, **Start Date: 12/31/1994, ***Start Date: 12/31/1999, ****Start Date: 7/31/2009.*

EXHIBIT 7

Active Risk Decomposition



principal components analysis (PCA) factors. As a result of our expected return overlay and the OutDex™ portfolio construction algorithm, we anticipate the majority of the tracking risk coming from company-specific events. Exhibit 7 shows the quarterly active risk decomposition of the OutDex™ Global Large Mid to S&P Global Large Mid Index for a 10-year period ending March 31, 2015.

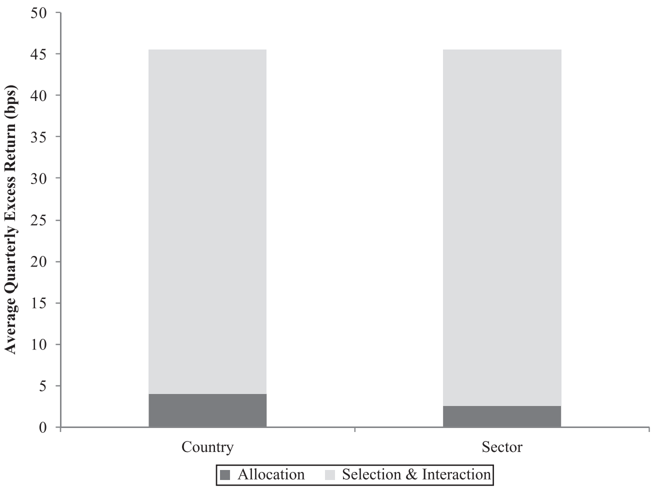
As expected, the decomposition of tracking risk in Exhibit 7 shows that stock-specific events account for 62.7% of total tracking risk on average over a 10-year period. To determine the source of the excess returns, we performed an attribution analysis on all our OutDex™ portfolios versus their underlying indexes based on the methodology proposed by Brinson and Fachler [1985] and Carino [1999]. We combined interaction effect with selection effect. Exhibit 8 shows the performance attribution of OutDex™ Global Large Mid versus the S&P Global Large Mid Index. We evaluated the impact of allocation to countries as well as sectors. The results are consistent with active risk decomposition presented in Exhibit 7. Over the 10-year period ending March 31, 2015, on average OutDex™ Global Large Mid outperformed the S&P Global Large Mid Index by 46 bps. For both countries and sectors, allocation impact accounts for approximately 9% and 6%, respectively, of the outperformance.

CONCLUSION

Our findings are based on an OutDex™ strategy using a traditional buy and hold portfolio construction method. We recognize the benefits associated with other investment vehicles (index funds, ETF, ETN, or other structured products) that would provide more efficient tax

EXHIBIT 8

Performance Attribution: OutDex™ vs. S&P Global Large Mid Index



and cost structures. We believe the concept of OutDex™ can be applied using these vehicles. By doing so, an additional study would be able to evaluate OutDex™ on an equal footing versus the aforementioned investment vehicles, accounting for performance, taxes, and costs. We provided evidence that OutDex™ strategies deliver statistically significant excess returns across various combinations of regions, countries, and sectors while closely tracking the underlying benchmark index.

APPENDIX

Measurement Statistics to Evaluate a Factor Selection

1. *Buy value added (BVA)* is defined as the spread of Quintile 1 average return to the model investable universe average return. A positive BVA indicates that the model is providing value whereas a negative BVA would indicate that the model is detracting value. BVA also allows for new relevant information to be captured by the model at each model update within any measurement period.

$$BVA = \frac{\sum_{1}^{n} R_{n(Q1)}}{n} - \frac{\sum_{1}^{u} R_{u(Universe)}}{u}$$

where,
R = Returns
n = total number of stocks in Quintile 1
u = total number of stocks in the Model Universe

2. *Torpedo avoidance value (TAV)* is defined as the spread of the model universe average return to Quintile 5 average return. A positive TAV indicates the model's torpedo counter-measures were effective in avoiding negative returns.

$$TAV = \frac{\sum_{1}^{u} R_{u(Universe)}}{u} - \frac{\sum_{1}^{x} R_{x(Q5)}}{x}$$

where,
R = Returns
u = total number of stocks in the Model Universe
x = total number of stocks in Quintile 5

3. *Persistent hit rate (PHR)* is defined as the total number of periods in which the selected quintile outperforms the universe as a percentage of the total number of periods. For example, if the equally weighted returns of Quintile 1 outperform the equally weighted returns of the universe in 20 out of 30 monthly periods, the persistent hit rate is 20 divided by 30 (66.67%).

$$PHR = \frac{B}{P}$$

where,
B = total number of stock ranking periods where BVA > 0
P = total number of stock ranking periods

4. *t-Statistic (t-Stat)* is a measure of the confidence interval for a given hypothesis test. The *t*-Stat is used to determine if excess return being provided by the model is significantly different from zero. For a 95% confidence level, the *t*-Stat value should not be between –1.96 and +1.96, allowing the rejection of the null hypothesis that excess return is zero.
5. *Information coefficient (IC)* is a measure of how a factor's or model's ranking score is correlated to subsequent returns. It is the correlation coefficient between the factor rank and the return rank for all companies in the universe for a specific period.

ENDNOTES

[1]The information ratio is equal to the information coefficient (IC) multiplied by the square root of market breadth. As reported by Grinold and Khan [2000], "A good forecaster has IC = 0.05, a great forecaster has IC = 0.10, and a world-class forecaster has IC = 0.15. An IC higher than 0.20 usually signals a faulty backtest or imminent investigation for insider dealing."

[2]A statistical dispersion, or an indication of how distant a portfolio's performance is from its benchmark, is called *tracking error*. Tracking error by itself does not indicate whether a portfolio is outperforming or underperforming its benchmark. However, a zero tracking-error portfolio will have a risk profile that is identical to its benchmark.

REFERENCES

Ang, A., R.J. Hodrick, Y. Xing, and X. Zhang. "High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence." *Journal of Financial Economics*, 91 (2009), pp. 1-23.

Aw, E.N.W., C.R. Dornick, and J.Q. Jiang. "Combining Quantitative and Fundamental Analysis: A Quant-amental Approach." *The Journal of Investing,* Vol. 23, No. 2 (2014), pp. 28-43.

Basu, S. "Investment Performance of Common Stocks in Relation to Their Price Earnings Ratio: A Test of the Efficient Market Hypothesis." *Journal of Finance*, Vol. 32, No. 3 (1977), pp. 662-82.

Bogle, J.C. "Selecting Equity Mutual Funds." *The Journal of Portfolio Management*, Vol. 18, No. 2 (1992), pp. 94-100.

Brinson, G. P., and N. Fachler. "Measuring Non-U.S. Equity Portfolio Performance." *The Journal of Portfolio Management,* Vol. 11, No. 3 (1985), pp. 73-76.

Carino, D. "Combining Attribution Effects Over Time." *Journal of Performance Measurement*, Vol. 3, No. 4 (1999), pp. 5-14.

Chen, N., R. Roll, and S. Ross. "Economic Forces and the Stock Market." *Journal of Business*, Vol. 59, No. 3 (1986), pp. 383-403.

Cremer, K.J.M., and A. Petajisto. "How Active Is Your Fund Manager? A New Measure That Predicts Performance." *Review of Financial Studies*, Vol. 22, No. 9 (2009), pp. 3329-3365.

Fama, E.F., and K.R. French. "Cross-Section of Expected Stock Returns." *Journal of Finance*, Vol. 47, No. 2 (1992), pp. 427-465.

Greenblatt, J. *The Little Book That Beats the Market*. Hoboken, NJ: John Wiley & Sons Inc., 2006.

Grinold, R. "The Fundamental Law of Active Management." *The Journal of Portfolio Management*, Vol. 15, No. 3 (1989), pp. 30-37.

Grinold, R., and R. Khan. *Active Portfolio Management*, 2nd edition. New York, NY: McGraw-Hill, 2000.

Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implication for Stock Market Efficiency." *Journal of Finance*, Vol. 48, No. 1 (1993), pp. 65-91.

Jones, R.C. "The Active versus Passive Debate: Perspective on an Active Quant." In *Active Equity Portfolio Management*, edited by Frank J. Fabozzi, Hoboken, NJ: John Wiley & Sons, 1998, pp. 37-56.

Kang, X., and D. Ung. "Practical Considerations for Factor-Based Asset Allocation." *The Journal of Index Investing*, Vol. 5, No. 4 (2015), pp. 33-47.

Naranjo A., A. Nimalendran, and M. Ryngaert. "Stock Returns, Dividend Yields and Taxes." *Journal of Finance*, Vol. 53, No. 6 (1998), pp. 2029-2057.

Sharpe, W.F. "The Arithmetic of Active Management." *Financial Analysts Journal*, Vol. 47, No. 1 (1991), pp. 7-9.

Soe, A. "The S&P Indices versus Active Funds (SPIVA) Scorecard." S&P Dow Jones Indices, March 2015.