

IS ACTIVE EQUITY MANAGEMENT ALPHA ON PERMANENT OR TEMPORARY DISABILITY?

April 2013

An examination of the changing relationships between Active Share and excess return for various active management strategies and the cyclical and structural factors behind them.

INTRODUCTION

In 2011, FIS Group published a research paper which analyzed the drivers of entrepreneurial (or smaller) manager outperformance in US equity strategies from 2006-2010.¹ While the study illustrated out-performance for five out of seven long-only equity investment styles offered through smaller managers/strategies (based on assets under management (AUM)) relative to their larger manager peers, it also detected the apparent beginnings of diminishing excess returns to fundamental active equity management strategies in the post-financial crash period. The most marked erosion of return has been observed among active Large Growth and Large Core products. By the end of 2012, the S&P 500 Index had risen over 100% since the market bottom in March 2009; but as a class, U.S. Large Cap active managers have been underperforming the market benchmark with a tenacity that is troubling. The paper analyzes several key questions including:

- **Are actively managed Large Cap strategies no longer a viable option due to structural changes in the market? Or, are these changes cyclical in nature?**
- **If the observed performance degradation is cyclical, which variables led to Large Cap products' underperformance? What factors would indicate the end of the cycle and when can we expect them?**

The 'Active Share' concept was developed by Yale University's School of Management Professors Antii Petajisto and Martijn Cremers and measures the degree to which the holdings of a portfolio differ from the relevant market benchmark. After examining the stock holdings of 904 U.S. mutual funds, Petajisto and Cremers' 2006 study demonstrated that Active Share had an apparent positive relationship with excess return. Specifically, their analysis of the holdings and performance data of 904 U.S. mutual funds between 1980 and 2003, found that funds in the highest quintile of Active Share outperformed their benchmarks annually by 1.39%, net of fees and expenses and that non-index funds with the lowest Active Share underperformed their benchmark by 1.41% annually, net of fees and expenses.²

This research paper evaluates whether the positive relationship between Active Share and excess return observed in the prior studies changed in the post 2008 financial crash era; and if so, what variables led to the change. Our research suggests that, while a ten year analysis yields results that are consistent with Petajisto and Cremers' study, over the last five years, the relationship between these two variables remained intact for actively managed Small Cap and Non-U.S. funds but grew insignificant for actively managed Large Cap funds. Partially in response to disappointing performance by Large Cap U.S. equity managers, institutional investors are increasingly moving towards passive implementation of their public equity allocations as well as alternative investments.

¹ Byles Williams, Tina, [Survival of the Nimble, Why Smaller Managers Outperformed Larger Managers Despite a Challenging Market Cycle for Active Fundamental Managers](#), April 2011.

² Petajisto, Antii and Cremers, Martijn, [How Active is your Fund Manager? A New Measure That Predicts Performance](#), March 2006.



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ABOUT FIS GROUP

FIS Group is a registered investment advisor specializing in entrepreneurial manager investment strategies with approximately \$3.4 billion* in assets under management and advisement. Our equity products include: Large Cap Core, All Cap Core, Small Cap Core, Small Cap Growth, Global Equity and Non-US Equity. Headquartered in Philadelphia, FIS Group was founded in 1996 by Tina Byles Williams.

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* Assets under management (AUM) are assets for which FIS Group has full discretion to hire and terminate sub-managers (\$2.6B as of 2/28/13). Additionally, the firm's AUM includes directly managed non-fee paying assets of \$1.3B as of 2/28/13. Investment advisory assets are all assets for which FIS Group has less than full discretion to hire or terminate sub-managers, but provides portfolio structure, manager recommendations and performance reporting (\$787M as of 2/28/13).

A structural impairment in the relationship between Active Share, active management strategies and excess return would indeed provide a strong case for employing index strategies. A cyclical change would support a case for maintaining some (although perhaps a smaller) allocation to active strategies to prepare for the eventual cyclical inflection. By examining the rolling performance trend in the rank of commonly used market benchmarks relative to their relevant universe of active management styles and asset classes, we identified less cyclical performance persistence among Non-U.S. and Small Cap managers but a cyclical pattern of outperformance/underperformance among Fixed Income and Large Cap managers relative to their market benchmark. Through a series of regression analyses, we further evaluated key variables that appear to drive the relative performance cycle for Large Cap managers in order to evaluate whether the recent cycle of underperformance is underpinned by structural or cyclical dynamics. Our analysis suggests that there are both cyclical and structural elements to cycles of active manager underperformance, with the most recent four plus year cycle distinguished by the dominant role of macro-economic policies. During the post financial crash period, we found that the three most harmful variables for Large Cap managers' relative performance were intra-market stock correlations (i.e., the degree of synchronicity with which individual stocks move relative to the overall market index); extreme performance divergence (where a handful of companies dominate the overall market's performance), and the level and change in liquidity in the financial system (a proxy for changes in monetary accommodation).

What was most noticeable about the current cycle of Large Cap manager underperformance relative to the earlier Tech-bubble period (when Large Cap managers also underperformed), is the outsized impact of macro or policy driven variables. This observation would suggest that their normalization could foreshadow a period of active management outperformance.

SECTION ONE: ACTIVE SHARE AND ALPHA REVISITED

The calculation for Active Share from Cremers and Petajisto's 2006 study is based on the proportion which a portfolio differs from its passive benchmark with a scale between 0% to 100%.³ A reading of 0% suggests that a portfolio's holdings are identical to the index; whereas a score of 100% connotes a complete contrast from the index. Funds with high Active Share distinguish their results from the benchmark either through selecting different stocks or by overweighting and underweighting industries relative to the benchmark.

Michael J. Mauboussin's and others work on various measures used for distinguishing between skill and luck for investment management and other activities posit that such measures should be both persistent and predictive. Because the Active Share of a portfolio is a direct result of a manager's investment process, one would expect substantial statistical persistence in this statistic over time. In fact, according to a study conducted by Mauboussin, the correlation of the Active Shares exhibited by almost 1500 mutual funds over the period between 2007 and 2012, was .86.⁴

While skill should be persistent, persistence does not necessarily cause or reveal skill. Specifically, for an individual manager, difference from the benchmark is not necessarily an indicator of skill, (in fact Cremers and Petajisto's study demonstrated that while high Active Share managers outperformed low Active Share managers on average, there was a great deal of variability in their performance). On the other hand, as discussed in Mauboussin's work, for activities that are highly impacted by random events over short or intermediate term periods, such as investing, long-term success is highly correlated to investment processes through which skill is persistently executed. Therefore, if a manager possesses true and relatively persistent skill, greater variation from the benchmark (i.e., higher Active Share), would be expected to amplify their return relative to their style peers who are equally skillful but exhibit little deviation from the holdings of benchmark over time. In fact, while Mauboussin's study found that the performance results from commonly used selection criteria such as risk-adjusted excess return (or alpha) and Morningstar ratings between the periods 2005-2007 and 2008-2010 exhibited substantial mean reversion (in that the performance of the highest ranking funds demonstrated negative correlation with the results for the second period), the correlation between Active Share and excess return over the study period was a respectable .27.⁵

³ Id.

⁴ Mauboussin, Michael J., *The Success Equation: Untangling Skill and Luck in Business, Sports, and Investing*, November 2012.

⁵ Id.

In **CHARTS 1 AND 2** we evaluated the relationship between mutual funds in Factset’s mutual fund and institutional database Active Share and their excess return and information ratio (which measures the efficiency or consistency with which a fund achieves excess return by dividing its excess return by its tracking error relative to the benchmark) for the trailing ten year period ending June 30, 2012. Consistent with Cremers and Petajisto, our analysis revealed a positive beta coefficient relationship between Active Share and excess return and information ratio.^{6,7}

CHART 1 Active Share and Excess Return
All Equity Mutual Funds for the Trailing Ten Years Ending June 30, 2012

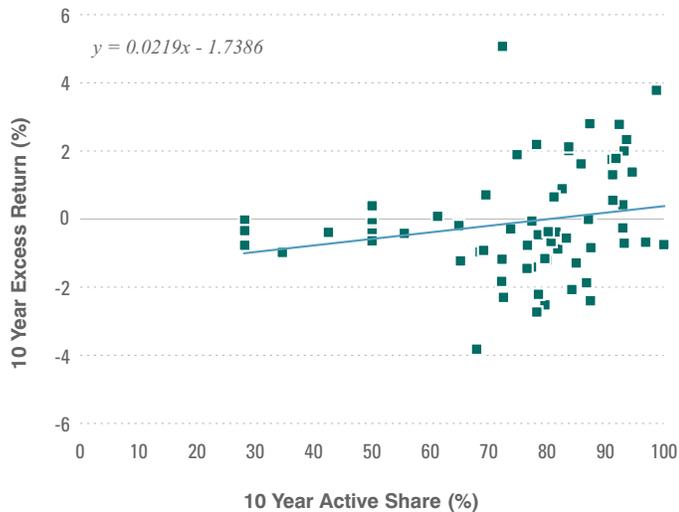
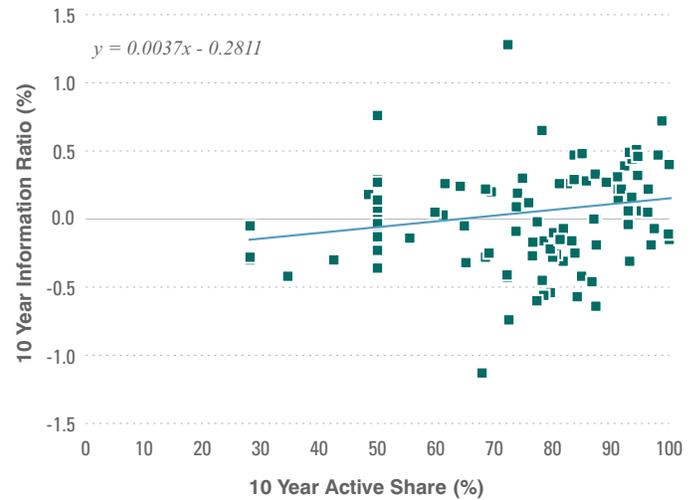


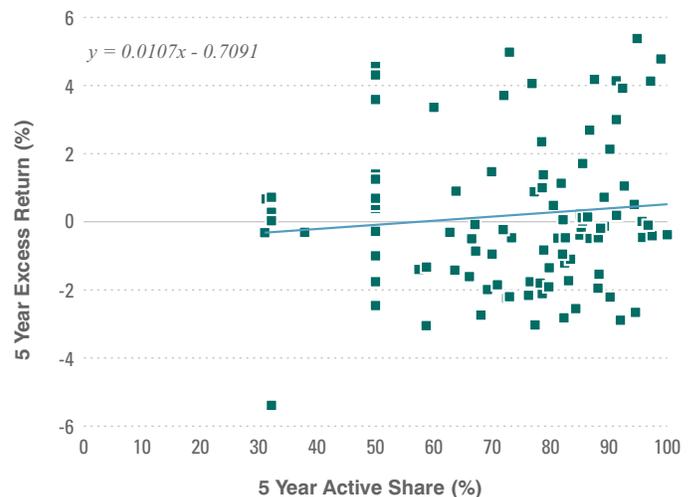
CHART 2 Active Share and Information Ratio
All Equity Mutual Funds for the Trailing Ten Years Ending June 30, 2012



We also broke the entire mutual fund universe into three styles, Non-U.S. equity, Small Cap and Large Cap funds. For all three styles, our analysis revealed a positive beta coefficient relationship between Active Share and excess return and information ratio.^{8,9} The strongest relationships were for Non U.S. and Small Cap funds and the weakest (though still positive) coefficients were exhibited by Large Cap funds.

The five year period ending June 30, 2012 exhibited somewhat weaker but still positive coefficient relationships between Active Share and excess return and information ratio for all mutual funds (see **CHARTS 3 AND 4**).

CHART 3 Active Share and Excess Return
All Equity Mutual Funds for the Trailing Five Years Ending June 30, 2012



⁶ Data reflected in Charts One through Eight was sourced through Factset Research Systems [Factset Mutual Fund & Institutional Database], retrieved October 1, 2012 to October 31, 2012, from Factset database. For the trailing ten year charts (charts One and Two), 100 funds were evaluated. For the trailing five years charts (charts Three through Eight), 150 funds were evaluated. For chart Nine (Active Share vs. product assets), 56 funds were evaluated.

⁷ Historical analysis of universe data is likely to reflect some degree of survivorship bias. This data source unfortunately did not allow us to correct for survivorship bias. However, since the primary point of this analysis is to compare the trend in the relationship among the different styles examined and there is no reason to believe that this bias disproportionately impacted any particular style, we believe that it is still relevant. Furthermore, our analysis on the rolling performance persistence of active managers within these style groups which did correct for survivorship bias is consistent with these results.

⁸ Data reflected in Charts 1-7 was sourced through Factset Research Systems [Factset Mutual Fund & Institutional Database], retrieved October 1, 2012 to October 31, 2012, from Factset database. For the trailing ten year charts (charts 1-6), 100 funds were evaluated. For the trailing five years charts (charts 7-12), 150 funds were evaluated. For chart 13 (Active Share vs. product assets), 56 funds were evaluated.

⁹ Historical analysis of universe data is likely to reflect some degree of survivorship bias. This data source unfortunately did not allow us to correct for survivorship bias. However, since the primary point of this analysis is to compare the trend in the relationship among the different styles examined and there is no reason to believe that this bias disproportionately impacted any particular style, we believe that it is still relevant. Furthermore, our analysis on the rolling performance persistence of active managers within these style groups which did correct for survivorship bias is consistent with these results.

However, while the trailing five year relationships between Active Share and both excess and information ratio remained positive for Non-U.S. and Small Cap funds they were insignificant for Large Cap funds. To illustrate, **CHARTS 5 THROUGH 9** compare these relationships among Non-U.S. equity and Large Cap funds for the trailing five years ending June 30, 2012.

CHART 4 Active Share and Information Ratio
All Equity Mutual Funds for the Trailing Five Years Ending June 30, 2012

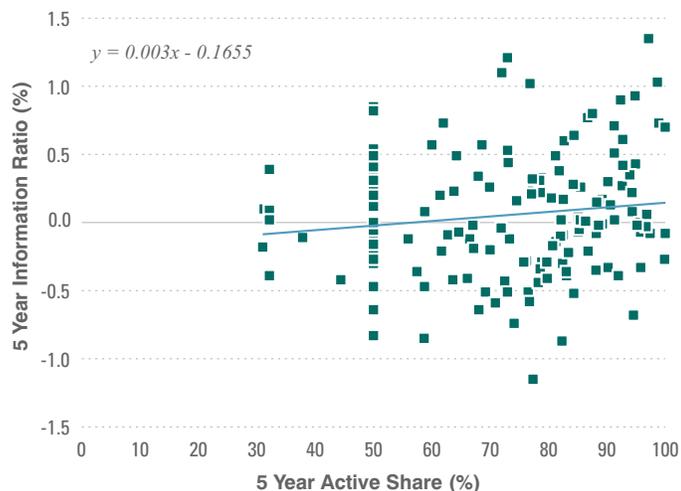


CHART 5 Active Share and Excess Return
Non U.S. Equity Funds for the Trailing Five Years Ending June 30, 2012

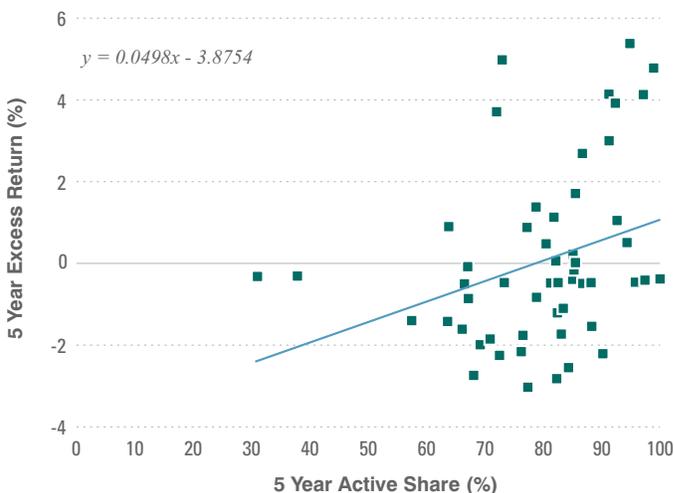


CHART 6 Active Share and Information Ratio
Non U.S. Equity Funds for the Trailing Five Years Ending June 30, 2012

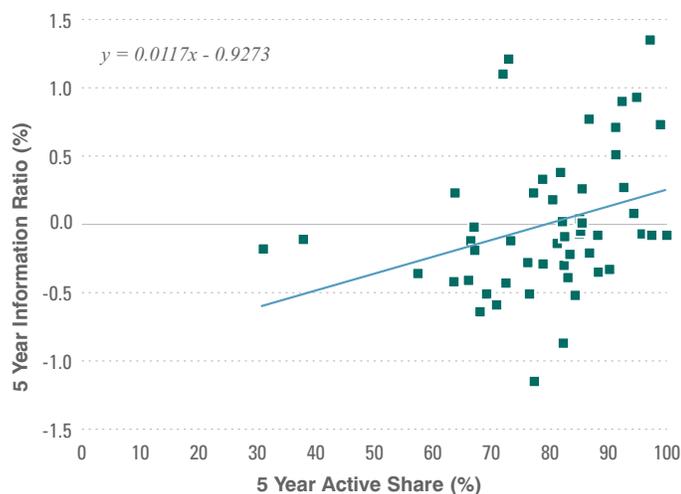


CHART 7 Active Share and Excess Return
Large Cap Active Funds for the Trailing Five Years Ending June 30, 2012

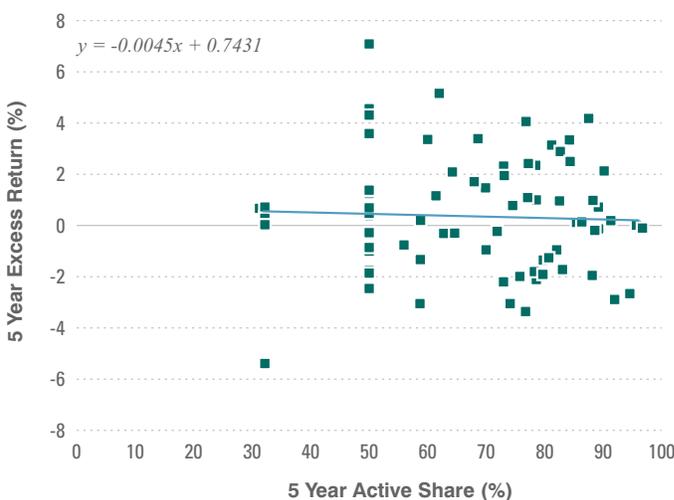


CHART 8 Active Share and Information Ratio
Large Cap Active Funds for the Trailing Five Years Ending June 30, 2012

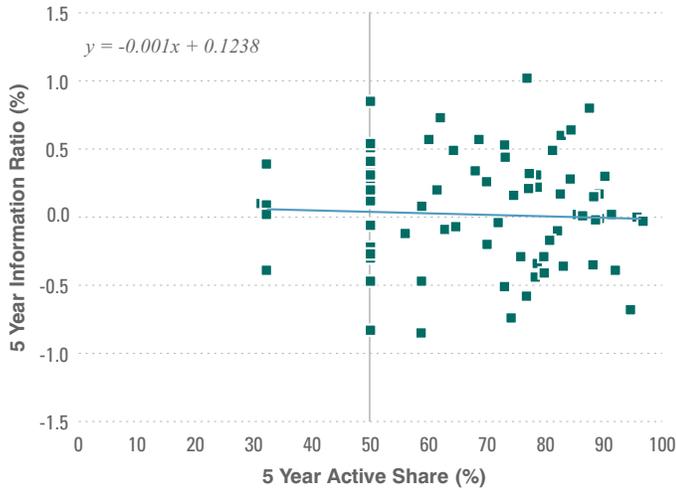
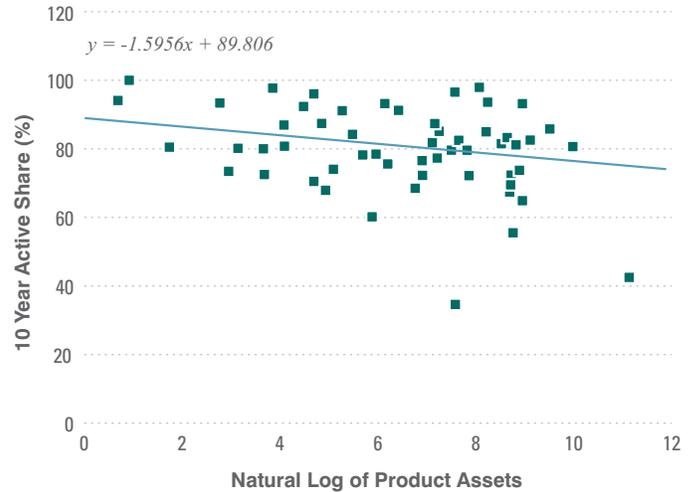


CHART 9 Product Assets and Active Share
Non U.S. Equity Managers for the Trailing Ten Years Ending June 30, 2012



The 2011 “Survival of the Nimble” paper examined the unique portfolio characteristics of smaller AUM managers that allowed them to outperform their mega-sized peers over the 2006-2010 study period. That research suggested that the key structural characteristics that advantaged smaller managers was their tendency to construct more concentrated and higher Active Share portfolios as well as their ability to trade more nimbly into less liquid securities within the market opportunity set.¹⁰ Accordingly, as shown in **CHART 9** above, our research on Active Share relationships suggests a negative relationship between Active Share and product AUM (represented as the natural log of product assets) for Non-US equity funds. A similar analysis for Large Cap funds also suggests a negative but weaker relationship between Active Share and product AUM. Since most Small Cap funds self-limit their product AUM growth, the relationship between Active Share and product AUM was inconclusive. As shown in **CHART 10**, these findings are consistent with our 2011 research on the difference in portfolio concentrations between small or entrepreneurial managers and their larger peers in that smaller managers tend to hold more concentrated portfolios that generally engender higher Active Share.¹¹

Therefore, to the extent that Active Share is not being rewarded and more diversified and index-like portfolios are, entrepreneurial or smaller managers would be expected to be disproportionately impacted.

Equity-focused hedge funds represent another type of strategy for which manager skill is largely expressed through trading and constructing high Active Share portfolios. In essence, hedge funds are active management strategies with more flexible portfolio construction and trading parameters. Therefore, the observed diminution in the relationship between positive excess return and high Active Share strategies for Large Cap equities would also be expected to impact certain equity-focused hedge funds that substantially trade Large Cap stocks. While the cyclical dynamics behind hedge fund returns are not examined in this paper, it is interesting to note that certain equity focused strategies (such as long-short, equity hedge and market neutral funds) have also experienced significant performance challenges over the last five years.

CHART 10 Number of Holdings
Five Years Ending December 31, 2010



^{10 & 11} Byles Williams, Tina, *Survival of the Nimble*

SECTION TWO: ROLLING PERFORMANCE TRENDS IN THE EXCESS RETURN GENERATED BY ACTIVE MANAGEMENT STRATEGIES

Examining the rolling performance trends in excess return for various active management strategies over the almost 20 year study period between January 1, 1993 and September 30, 2012 provides a historical context for evaluating the recent cycle of diminished alpha for active managers. **CHARTS 11 THROUGH 16** provide the historical performance trend for commonly used market benchmarks that represent the passive alternative for various asset class and style segments relative to the universe of active managers for that segment. The universe data is based on Wilshire Associates' Manager Defined Separate Account Universe from that firm's Compass database. In order to reduce survivorship bias, we incorporated both active and inactive products in the Wilshire Compass database. While we have attempted to correct for survivorship bias, it is important to note that like many time series studies that estimate multiple-period trends, this analysis would be expected to embody a moving average error term that is engendered by using overlapping data. That is to say that each subsequent data point for rolling 12 quarter data is not totally independent from the prior 11 periods. In our regression analysis in Section Three we attempt to adjust for this moving average error term by incorporating it in the model.¹²

CHARTS 11 AND 12 examine the historical trend of the Non-US and Small Cap benchmarks relative to their respective universe of active managers. We used the Russell 2000 Index to evaluate Small Cap managers and the MSCI EAFE Index to evaluate Non-US managers.¹³ For the latter, we only used managers who invested in developed country non-U.S. markets, because historical universe data for more broadly based non-U.S. strategies (that are more appropriately benchmarked against the ACWI non-U.S. benchmark) was insufficient.

CHART 11 Rolling 12-Quarter Universe Analysis
December 31, 1992 to September 30, 2012
Wilshire Manager Defined EAFE Universe

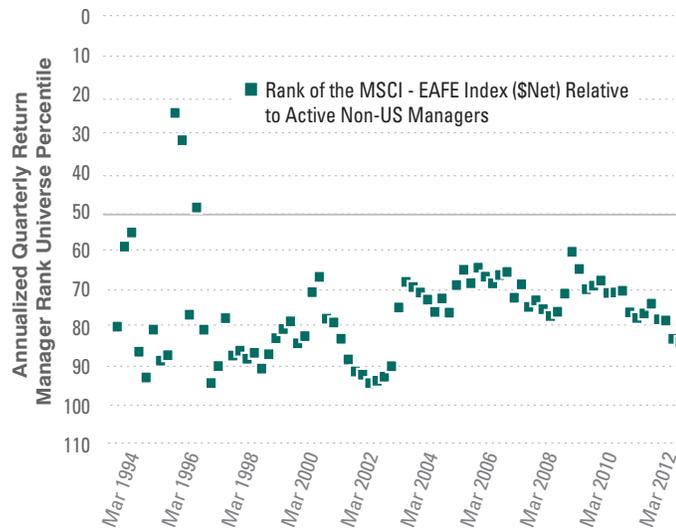
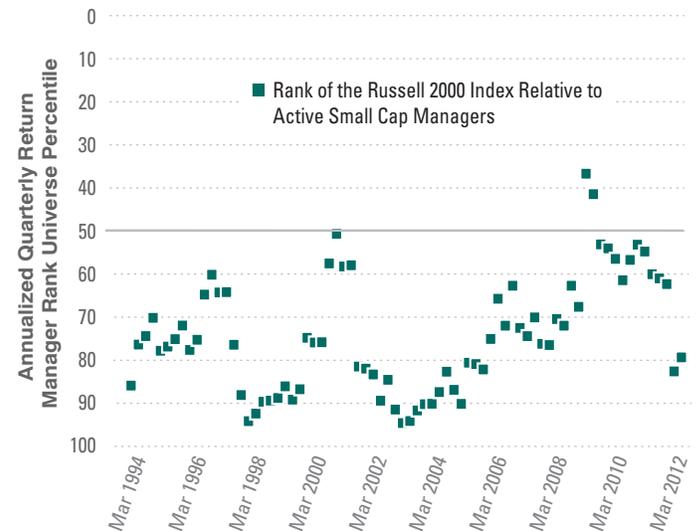


CHART 12 Rolling 12-Quarter Universe Analysis
December 31, 1992 to September 30, 2012
Wilshire Manager Defined Small Core Universe



The data illustrates that throughout most of the period, both benchmarks ranked below the median manager within their respective universe of active managers. For both Non-US and Small Cap managers, the pattern of excess returns suggests both persistence and minimal cyclicity.

¹² See for example, Hansen, Lars Peter and Hodrick, Robert J., *Forward Exchange Rates as Optimal Predictors of Future Spot Rates: Econometric Analysis*, *The Journal of Political Economy*, Vol. 88, No. 5, (October 1980) and Harri, Ardian and Brorsen, B. Wade, *Quantitative and Qualitative Analysis in Social Sciences*, Volume 3, Issue 3, 2009

¹³ Source for all universe analyses (Charts Eleven through Sixteen) is Wilshire Associates' Manager Defined Separate Account Universe, Wilshire Associates' Compass Database

CHART 13 shows a similar analysis for active Fixed Income strategies. The relative performance of Fixed Income managers appeared to be more cyclical in nature. While the factors determining the excess return of Fixed Income managers were not evaluated in our statistical analysis, the common denominator for the two periods in which the benchmark Barclays Aggregate rose well above the median active manager to the first quartile appears to be a loss of investor confidence in credit risk. The first period of active Fixed Income manager underperformance coincides with the 2001-2002 period of major accounting scandals among large corporations which undermined the market's confidence in corporate credit risk. The second period was the 2008 credit crisis. During the most recent three year period, the Barclays benchmark has been a relatively easy benchmark to beat in that it has been below the median manager and is now in the bottom quartile. Fixed Income managers have likely benefitted from the fairly persistent out-performance of being long credit and duration as a result of extraordinarily accommodative monetary policy easing after the 2008 financial crisis.

CHARTS 14 THROUGH 16 evaluate the trailing benchmark performance for Large Cap managers.

CHART 13 Rolling 12-Quarter Universe Analysis

December 31, 1992 to September 30, 2012
 Wilshire Manager Defined Core Plus Universe

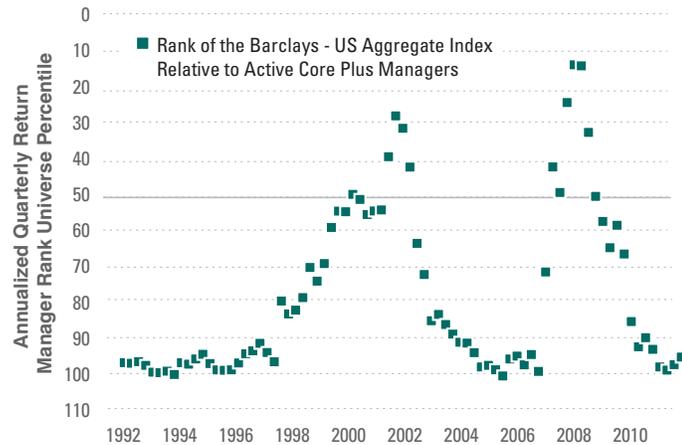


CHART 14 Rolling 12-Quarter Universe Analysis

December 31, 1992 to September 30, 2012
 Wilshire Manager Defined Large Core Universe

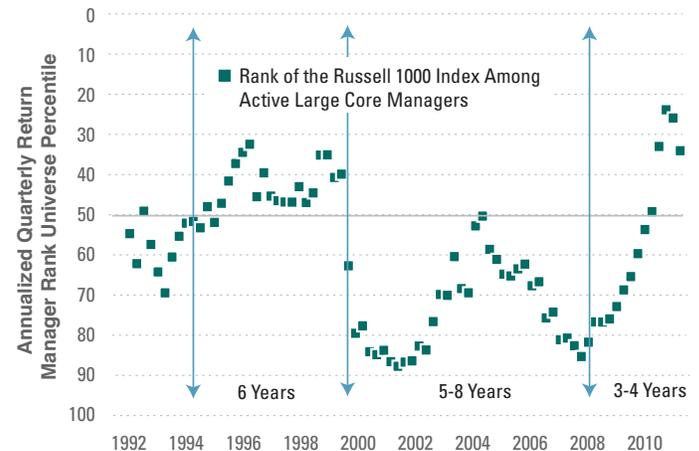


CHART 15 Rolling 12-Quarter Universe Analysis

December 31, 1992 to September 30, 2012
 Wilshire Manager Defined Large Growth Universe

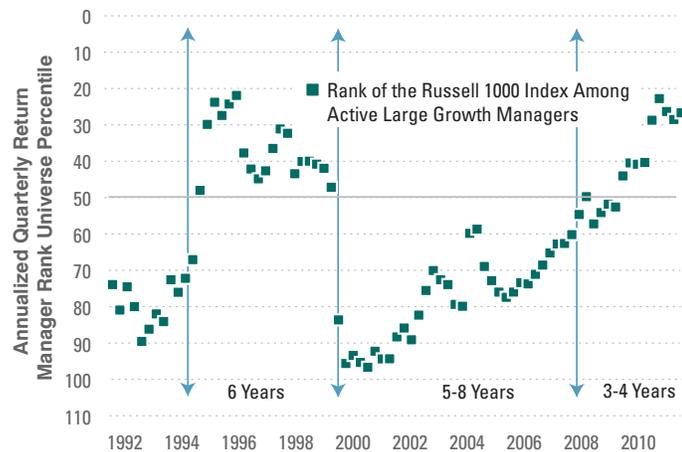
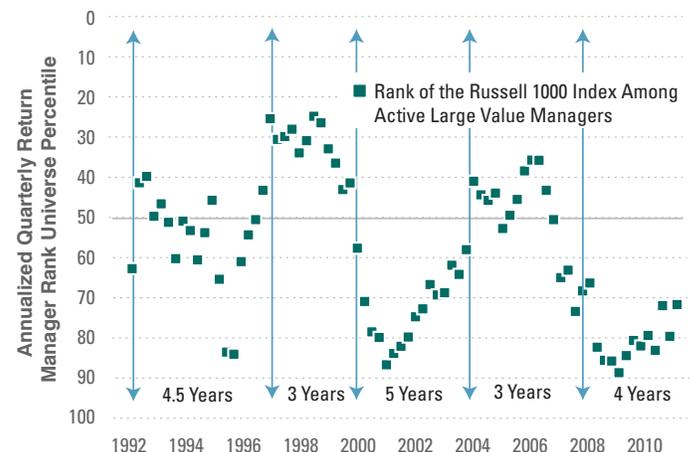


CHART 16 Rolling 12-Quarter Universe Analysis

December 31, 1992 to September 30, 2012
 Wilshire Manager Defined Large Value Universe



For all Large Cap styles, the ranking of the respective benchmark relative to the universe of active managers clearly suggests cyclicity in that periods in which the benchmark ranked above the median manager were followed by its descent to a below median ranking. We believe that these trends reflect U.S. Large Cap stocks' greater exposure to systematic market risks relative to Small Cap and Non-U.S. stocks; which renders them relatively more vulnerable to changes in the macro-economic regime. **CHART 14** on the previous page shows two periods of outperformance for active Large Core managers. The first period precedes the mid-1990's that appears to demarcate the run-up in stock prices that ultimately culminated in the Tech bubble. The second period was after the burst of the Tech bubble in 2001 which persisted until 2009 when risk assets rallied in response to aggressive Fed accommodation (this was also the case in 2003). During the most intense phase of market stress (for example, the years 2001 and 2008), the Russell 1000 Index was in the bottom quartile of active managers; suggesting that active managers portfolios' variance from the market benchmark (i.e., their Active Share), protected assets during extreme market declines.

For Large Core managers, periods of persistent out/under-performance averaged around 6 years. Large Value managers appeared to experience shorter cycles while Large Growth managers experience longer cycles. For the most recent cycle of Large Cap manager underperformance, Large Value managers have fared relatively well relative to the Russell 1000 Value index, but Large Growth managers have experienced the longest and most severe underperformance relative to the Russell 1000 Growth index.

Section Three evaluates the factors behind the observed pattern of cyclicity for Large Core managers through a regression analysis in which the rank of the Russell 1000 index is analyzed as the dependent variable.

SECTION THREE: REGRESSION ANALYSIS

Our analysis of the time series performance data in excess returns for the strategies examined in Section Two suggests structural performance persistence for Non-US and Small Cap managers and a more cyclical pattern of performance for Fixed Income and Large Cap managers. This section provides the results of the regression analysis that evaluates the factors behind the observed pattern of cyclicity in the excess return of Large Core managers.

The methodology used for our regression model is discussed in greater detail in Appendix A. The dependent variable in our regression analysis was the rank of the Russell 1000 index over trailing twelve month periods relative to the universe of active Large Core managers in the Wilshire separate account database from January 1993 through September 2012. As previously mentioned, using overlapping periods in the estimation of time series models creates a moving average (MA) error term engendering serial correlation which biases ordinary least squares (OLS) estimates. We addressed this error by including the moving average error term in the model to adjust for serial correlation. The result was a more normally distributed residual error term. Additionally, our regression and variable co-integration analysis for the entire period suggested a fairly significant shift in the 'goodness of fit' for the model that seemed to coincide with the 2008 financial crisis. This observation led us to break our analysis period into two parts. The first period which begins in December 1993 and ends in September 30, 2012 and second period, labeled as the post-crisis period, begins in January 2007 and ends on September 30, 2012.

We initially evaluated sixteen (16) variables to determine their individual relationship and level of significance relative to the dependent variable. A description of each variable and the process through which we evaluated them is provided in Appendix A. Our final list of input variables is as follows:

1. FIS Group Liquidity Cycle Indicator (Liq. Cycle)
2. Russell 1000 Big minus Small Trailing 12M Spread (Big vs. Small)
3. Russell 1000 Top 5 minus Bottom 5 Trailing 12M Spread (Top5 vs. Bott5)
4. FIS Group Profit Cycle Indicator (Prof. Cycle)
5. Russell 1000 index Top 2 Sectors minus Bottom 2 Sectors Trailing 12M Spread (Top2 Spread)
6. Large Cap Correlation (measured monthly)
7. US Economic Policy Uncertainty Index®
8. Trailing 12M turnover of the stocks in the top decile of the Russell 1000 index

The regression results for the entire analysis period as well as the post-crisis sub-period are summarized in **TABLE 1**.¹⁴ The table also provides our evaluation of the cyclical vs. structural nature of each independent variable used in the model. Based on their

respective F statistic and P values, one can observe that each of the models is statistically significant. (The threshold levels for significance for the F statistic and P value are greater than four and less than five, respectively). Further, comparing the adjusted R²s for each model suggest that both models robustly explain the variation of the rank of the Russell 1000 index.

TABLE 1 Summary of Regression Model Results for Russell 1000 Index Rank Among Large Core Managers and Our Observations

	Entire Period 12/93 to 9/12 Coefficient/T Stat Significance	Post-Crisis Period 1/07 to 9/12 Coefficient/ T Stat Significance	Nature of Variable
Model Adj. R ²	90.28%	94.51%	Both models significant
Significance F stat/P value	27.78 / 0.00	87.63 / 0.00	Models well above thresholds denoting significance
Intercept	97.72 / 9.88	135.86 / 8.99	
Moving average error term	.90 / 31.59	.61 / 6.34	Estimate of the portion of MA error carried over from prior periods to account for the use of rolling data. Adjusts for serial correlation induced by overlapping periods.
Description of the Independent Variables Selected for the Models			
1 Level/Change in monetary liquidity	0.39 / 6.51	(0.59) / (4.72)	Macro-driven & Cyclical. Normalization of monetary policy would reduce impact.
2 Intra-market stock correlation	(0.4) / (5.81)	(3.81) / (7.42)	Macro-driven & Cyclical but some structural increase likely
3 Economic Uncertainty	n/a	1.01 / 7.45	Macro-driven and cyclical. Current level of elevated uncertainty primarily driven by political and economic dislocation engendered by global deleveraging cycle.
4 Level/Change in profit cycle	n/a	1.24 / 8.14	Fundamental & Cyclical
5 Big caps outperform small cap stocks	(0.45) / (5.38)	1.92 / 7.37	Fundamental & Cyclical. Historical evidence of rotation between big and small cap stocks.
6 Return Dispersion. (Spread between the performance of top 5 vs. bottom 5 stocks)	(0.33) / (4.55)	(1.13) / (10.01)	Fundamental. Cyclicity depends on changes (and in this case) normalization of market volume/breath
7 R1000 top decile trailing 12 month turnover	(0.95) / (4.3)	(0.54) / (1.86)	Fundamental & Cyclical
8 Sector Dispersion. (Spread between the performance of top 2 vs. bottom 2 sectors).	(0.07) / (0.5)	n/a	Fundamental & Cyclical

First, since the lower the rank of the index, the better its performance relative to the universe of active Large Core managers, a negative beta coefficient would improve the relative rank of the index and impair the relative rank of active managers. Correspondingly, a positive beta coefficient impairs the relative rank of the index and improves the relative rank of active managers. Second, it should be noted that the first three variables are driven by policy or macro-driven dynamics while the last five variables are driven by fundamental market dynamics.

The regression fit lines for each of the periods delineated in **TABLE 1** are depicted in **CHARTS 17 AND 18** on the next page.

¹⁴ Sources for the data used in the regression analysis (Table Two and Charts Fifteen through Seventeen) are: 1) Wilshire Associates' Manager Defined Separate Account Universe from the firm's Compass database for the rank of the R1000 index relative to active Large Core managers; and 2) For the independent variables, Bloomberg, Factset, the Economic Policy Uncertainty Index website as well as FIS Group estimates.

CHART 17 Regression Fit
For the October 1994 to September 2012
Total Period



CHART 18 Regression Fit
For the January 2007 to September 2012
Post Crisis Total Period



SECTION FOUR: INTERPRETATION OF THE MODEL RESULTS

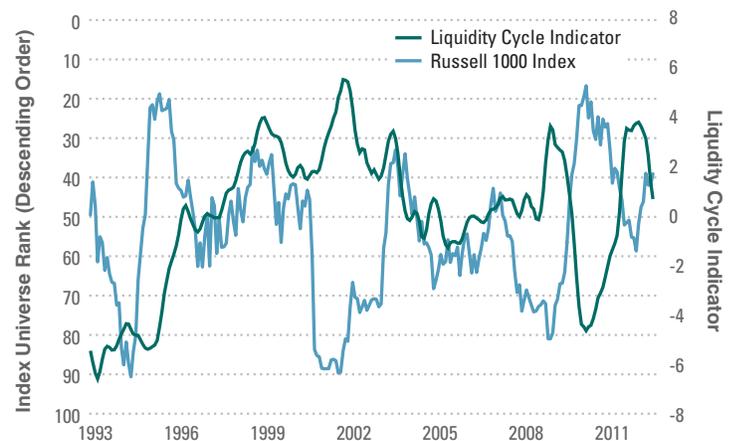
When comparing the two periods, the most notable changes that impaired the relative performance of active managers was the marked increase in the (negative) impact of stock correlations; the reversal of the monetary liquidity variable from a positive to a negative contributor as well as the tripling of the coefficient measuring the return dispersion between the top five and bottom five stocks of the market index (which impairs the relative performance of active managers). The following is a more detailed interpretation of the regression results for each independent variable as well as an evaluation of the key drivers behind that variable.

1. LEVEL AND CHANGE IN MONETARY LIQUIDITY

FIS Group’s liquidity indicator represents the smoothed difference between short-term growth in M2 and its long-term trend growth. This variable is largely driven by cyclical dynamics in the broad economy, that in effect, reflect the level of and change in monetary accommodation in the economy. For the entire period, this indicator had a positive relationship with the relative return of Large Cap managers. However, during the post 2008 post-crisis period, it turned sharply negative.

As shown in **CHART 19**, which compares the trend in this indicator to the relative rank of the Russell 1000 index among active Large Core managers, this inverse or negative relationship appears to be most pronounced during periods of economic or market stress; as in the years 2000 and 2008. At the point of maximum stress, liquidity drops precipitously and active managers substantially outperform the index (for example, the worst post crisis rank for the index was in late January 2009). Once the Fed’s accommodation gathers sufficient steam, the rank of the index subsequently rises rapidly relative to active managers. This is because aggressive Fed accommodation

CHART 19 Comparison of FIS Group’s Liquidity Indicator vs. Rank of the R1000 Index Rank Among Active Large Cap Managers



punishes the return on low risk assets (such as near-cash products), reduces the cost of leverage, and inflates the relative return on risky assets and strategies (such as lower quality debt and equity instruments as well as companies). Since most equity investment managers favor companies that demonstrate either or both earnings and balance sheet quality, periods of extreme monetary accommodation tend to impair their performance. During the post-crisis period, both the intensity and scope of monetary accommodation measures are unmatched for the 19 year study period. Accordingly, in addition to the change in its sign, both the magnitude and significance of this variable increased during the post-crisis period. These results would suggest that monetary policy normalization could presage a period of active manager outperformance.

2. INTRA-MARKET STOCK CORRELATIONS

This variable, which represents the correlation among Large Capitalization stocks, is by far the most significant for both periods and demonstrated a notably negative relationship with the relative performance of Large Cap active equity managers. Elevated correlations negatively impact the security selection alpha of active managers because fundamental factors (such as profit levels, valuations, etc.), which most active managers evaluate in order to generate alpha are overwhelmed by generalized movements in the market. Both the magnitude and significance level of this variable markedly increased during the post-crisis period when it was by far, the most damaging to the relative performance of active managers. Consequently, we believe that any possible resumption in the cycle of large equity active managers' outperformance would depend on whether post-crisis correlations represent a "new normal" or simply a long-term headache from a credit-fueled growth binge.

In light of this variable's significance to the performance success of active management strategies, we believe a more detailed analysis of its drivers is critical to understanding the conditions under which the current trend of underperformance will change. We believe that the observed increase in stock correlations is being driven by a combination of structural and cyclical factors.

Structural Factors

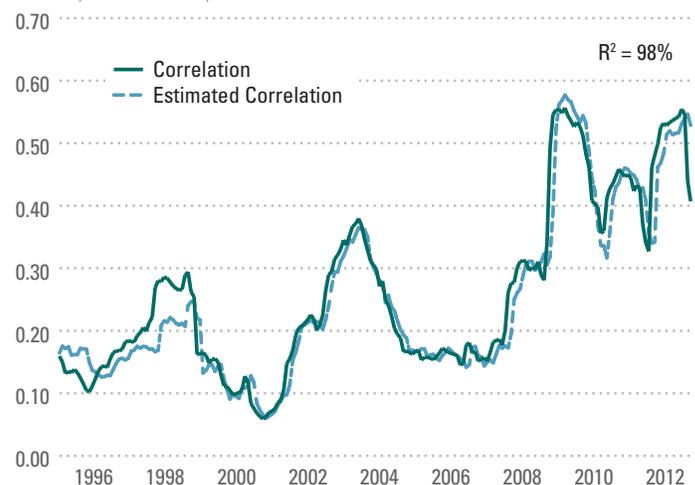
When investors trade an S&P 500 futures contract, they effectively place an order on all 500 constituent stocks and drive up correlations. Broad index products such as ETFs can have a similar effect. Additionally, systematic trading methods such as high frequency trading (HFT) would also be expected to heighten correlations. For example, HFT arbitrage strategies that seek to profit from divergences in the prices of individual stocks or groups and the actual index would tend to increase correlations. For the five years ending December 31, 2012, the volume of Electronically Traded Funds (ETFs) traded, (which can also facilitate index trading), grew by 70.85%. By the fourth quarter of 2012, index futures were about 187% of cash equity volume with growth in this instrument primarily fueled by the increased use of index trading strategies and high frequency trading. ETFs were less important drivers of heightened correlations because they accounted for 26% of cash equity volume. Additionally, about 31% of those ETFs were more specialized, such as sector ETFs, which would have the effect of driving down individual stock correlations while heightening inter-sector correlations.¹⁵

Cyclical Factors

During periods of high macro uncertainty, stock prices are largely driven by macro forces and as macro regimes change, stock prices move in unison. During such periods, systematic trading strategies discussed above serve as self-reinforcing mechanisms to further heighten correlations. In a separate regression model, the results of which are depicted in **CHART 20**, we attempted to understand the cyclical drivers of stock correlations. The dependent variable in the model is the average correlation between stocks in the Russell 1000 Index.

CHART 20 Actual vs Estimated Correlation

February 2, 1995 to September 28, 2012



¹⁵ Source for ETF data is http://www.blackrockinternational.com/content/groups/international/site/documents/literature/etfi_globalhandbook_2012.pdf. Source for S&P Futures data is <http://www.world-exchanges.org/statistics/monthly-reports>.

It is based on a calculation of correlations derived using the daily weights and pricing of the stocks in the Russell 1000 index between July 1980 and September 2012. The period prior to December 1998 uses a subset of stocks in the Russell 1000 while the remaining data is calculated using all constituents.

As shown in **CHART 20**, our model explains 98% of the variation in realized correlations.¹⁶

Importantly, the independent variables used in this model are primarily cyclical and not structural in nature. The correlation model is underpinned by the following formula:

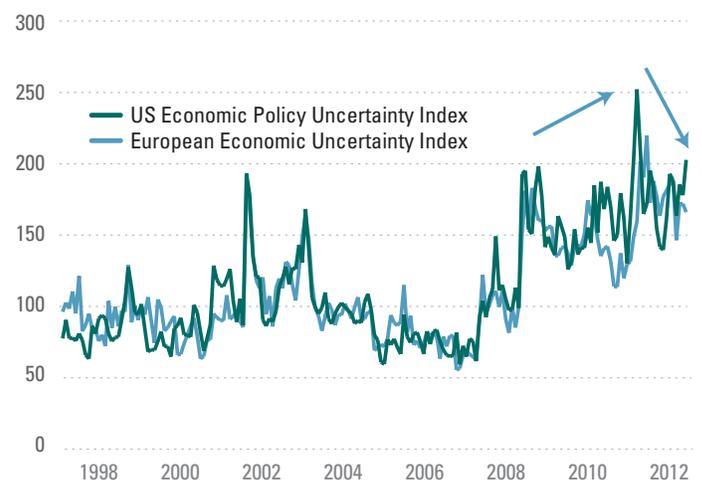
$$\text{Corr}_{(t+1)} = \text{Constant} + B_1 * \text{Corr}_{(t)} + B_2 * \text{DD}_{(t)} + B_3 * \text{EURI}_{(t)} + B_4 * \text{VoV}_{(t)}, \text{ where:}$$

1. **Constant**: captures the base level of correlation that would exist absent the effects of other variables
2. **B₁*Corr_(t)**: this term captures the effects of Correlation and contributes to the ‘clustering’ effect seen in correlation and volatility.
3. **B₂*DD_(t)**: this term captures the effect of downside deviation in the stock market. Throughout the life of the model, the beta to downside deviation is positive which suggests that increases in Downside Deviation lead to increases in Correlation. Given that Downside Deviation is often associated with negative market returns, the economic intuition behind the relationship makes sense.
4. **B₃*EURI_(t)**: this term captures the relationship between Correlation and Economic Uncertainty. Throughout the model, the beta between the two variables is positive but is non-linear. This suggests that Economic Uncertainty serves to increase correlation but that declines in Economic Uncertainty have a less powerful linear relationship in decreasing correlations. This makes economic sense and is consistent with what we have observed empirically since 2010. The non-linear relationship also makes sense in that based on behavioral finance research, investors tend to respond more dramatically to negative shocks than to gradual positive improvements.¹⁷
5. **B₄*VoV_(t)**: the volatility of stock volatility captures the mean reverting effects of correlation. Throughout the model the beta is negative. During periods of heightened VoV (coincident with heightened Downside Deviation), the VoV functions as a reversionary force to pull correlation back towards its mean.

Therefore, while structural changes and the growth of index-based trading instruments have likely raised the level of correlations beyond normative levels prior to 2006, with increased macro certainty (which would be captured by decreases in the Index of Economic Policy Uncertainty®), the mean reverting VoV variable in the cyclical structure of correlations would likely act as a self-reinforcing force to reduce correlations. However, the one variable in the correlation model whose long-term trend is unknown and certainly up for debate is economic policy uncertainty.

CHART 21 shows that the Economic Policy Uncertainty Index has indeed subsided over the last two plus years. The high degree of synchronicity between the Economic Policy Uncertainty Indices for the U.S. and Europe shown in the chart depicts the tight feed-back loop relative to perceptions of policy uncertainty among Western developed countries. Deleveraging among the major developed nations has been both disruptive and contagious because of the highly globalized nature of their trading relationships and banking systems. As global capital markets have become more connected, the possibility that local financial shocks propagate more quickly to other regions has also increased. (For example, despite the fact that the GIIPS countries account for less than 6.3% of global GDP -- with Greece and Ireland accounting for 1%-- their sovereign debt crisis has threatened several meltdowns in global risk assets). In light of

CHART 21 European and U.S. Economic Policy Uncertainty Indices January 1997 to November 2012



¹⁶ Data sources for the correlation model were derived from Bloomberg, the Economic Policy Uncertainty Index website, Factset and FIS Group estimates

¹⁷ Azzopardi, Paul V., *Why Financial Markets Rise Slowly but Fall Sharply: Analyzing market behavior with behavioral finance*, December 28, 2012

the inherent political and macro-economic instability caused by deleveraging among major developed economies, it is likely that returning to the calmer pre-crisis levels of economic certainty (and equally importantly, a generalized perception of economic certainty), will be a gradual and multi-year proposition. Consistent with our regression analysis, correlations have indeed subsided somewhat along with the decline in economic uncertainty; but as a result of the previously discussed non-linear relationship, they will probably decline more gradually than their dramatic 2008 rise, as skepticism with respect to improvements in the market environment slowly subsides.

3. ECONOMIC UNCERTAINTY

The Economic Uncertainty Variable is the final macro driven variable. This variable is based on the US Economic Policy Uncertainty Index® which is designed to measure policy-related economic uncertainty. As discussed previously, this variable has a positive relationship with stock correlations but as a stand-alone variable, positively impacted the relative performance of active managers. We believe that this latter relationship reflects a historical pattern of active management outperformance (relative to market benchmarks) during periods of adverse economic and market circumstances. For example, during the 2001 through 2002 recession following the bursting of the Tech Bubble, the Russell 1000 benchmark was in the bottom quartile of active Large Core managers. This was also the case in 2008.

4. LEVEL AND CHANGE IN THE PROFIT CYCLE

Our profit cycle indicator represents a standardized measure of the spread between current earnings yield expectations versus expectations 12 months ago and is designed to represent the relative cyclical position of corporate profits. For the entire period model, this variable was not significant but displayed a positive coefficient relationship with the return of active managers during the post-crisis period. We believe that these results reflect the following two factors:

- a. the entire period result was likely substantially influenced by the run-up to the Tech Bubble and the post-Tech Bubble period of accounting scandals among some major corporations. During the run-up to the Tech Bubble, increases in stock prices were not necessarily driven by earnings but by anticipated earnings for dot.com companies. During the post-Tech Bubble period of accounting scandals, the market's trust in the quality of earnings was undermined; and,
- b. the second period has been dominated by strong earnings growth; first as a result of drastic cuts in the cost of labor and debt financing and later in the period, by growth in top line earnings or sales.

5. BIG CAPS OUTPERFORM SMALL CAPS

Among the fundamental variables, this variable, which is based on the spread between the trailing 12 month return of the top quintile and the bottom quintile of companies in the Russell 1000 Index based on market capitalization, was the most impactful. This variable had a negative coefficient during the entire period, suggesting that outperformance of Large Cap stocks relative to Small Cap stocks improves the relative rank of the index. However, during the post-crisis period, the sign of the beta coefficient turned positive. We believe that these results reflect the following two factors:

- a. the portfolios of most active managers tend to have a smaller average and median capitalization than their respective index (and by definition, passive managers). Therefore, when Large Cap stocks outperform Small Cap stocks, one would expect active managers to underperform, leading to a negative beta coefficient for the entire period; and
- b. For the post-crisis period, Large Cap financial stocks were at the epicenter of the 2008 market crash. Therefore, our observation of active managers' tendency to hold smaller capitalization stocks (even if they were in the financial sector), would have buoyed their performance relative to the market benchmark; thus leading to a positive beta coefficient.

6. RETURN DISPERSION

The spread between the trailing 12 month performance of the top five securities and the bottom five securities in the index

had a consistently negative coefficient. For the post-crisis period, both the magnitude and significance level of this variable substantially increased. This suggests that highly concentrated markets in which one or a handful of stocks are driving the performance of the entire index impair the relative performance of active managers. By employing investment processes that select a subset of the market opportunity set of securities (that constitute their particular benchmark index), active managers have a lower probability of holding the security dominating the market benchmark than the market benchmark itself which, by definition, is comprised of all its constituents. During declining markets, this dynamic typically benefits the relative performance of active managers. However during rising markets (particularly those with significant upward momentum), it typically impairs their relative performance. A recent anecdotal example of this phenomenon is the impact of Apple which at its September 18, 2012 height, represented almost 9% of the Russell 1000 Growth Index and accounted for over 400 bps. of the index's performance between January 1 and September 18, 2012. For the Russell 1000 Index, Apple accounted for almost 4% of its capitalization at the September 18 peak and over 200 bps. of its performance year to date. Common institutional guidelines that limit a manager's holding in a single security to between 3% and 5% of the market value of their portfolio would have obviously impaired performance relative to the benchmark during this period. This particular phenomenon is one of the reasons why we believe Large Growth managers were especially challenged over the last five years.

7. TOP DECILE TURNOVER

This variable represents the monthly turnover of the top decile of stocks in the Russell 1000 Index using the trailing twelve month return as the relevant metric. It demonstrated a negative relationship with the performance of active managers for both the entire period and the post-crisis period. To the extent that the market is trendless and there is extreme volatility among the factors and securities driving the market, managers would be expected to struggle because the opportunity to earn positive excess return from security selection is diminished.

8. SECTOR DISPERSION

This variable, which represents the spread between the trailing 12 month return of the top two minus the bottom two performing GICS sectors in the Russell 1000 Index, was insignificant in both of the sub-periods but had a positive and significant coefficient for the entire period. This would suggest that over-weighting/avoiding the best/worst performing sectors improved the performance of active managers relative to the index.

CONCLUSION

In Section One, we observed trends in the relationship between Active Share and excess return for actively managed equity mutual funds, (Small Cap, Large Cap, and Non-US equity) over trailing ten and five year periods ending June 30, 2012. While the results for the ten year period are consistent with Petajisto and Cremers' conclusions; the five year period suggested insignificant relationships between Active Share and excess return and information ratio for Large Cap equity funds. Given the previously mentioned importance of macro-variables in eroding the post 2008 relative performance of active managers, it is likely that U.S. Large Cap stocks' greater exposure to systematic market risks relative to Small Cap and Non-U.S. stocks made them more vulnerable to deleterious changes in the macro-economic regime. Large Cap stocks are also more vulnerable to structural market changes, such as the increasing use of index-based or ETF trading strategies, that as discussed previously, help increase correlations.

In Section Two, we examined the historical trends in the excess return for various active management strategies over the almost twenty year study period in order to provide a historical context for answering this question. Based on data which ranked the index for various market styles relative to the relevant universe of active managers in Wilshire Associates' separate account database, we concluded that for both Non-US and Small Cap managers, the pattern of excess returns suggests both persistence and minimal cyclicalities (i.e., these strategies' excess return appears to be more structural).

The performance of Large Cap managers relative to the Russell 1000 benchmark exhibited a clear pattern of cyclicalities with each cycle lasting about five to seven years. The two particularly difficult periods for Large Cap managers were between 1995 and 2000 (i.e., during the Tech Bubble) and the last four years. For the period between 2001 and 2008, (other than a clear interruption

in 2003, which represented the maximum thrust of aggressive monetary accommodation in response to the 2001 recession), the benchmark was below the median Large Cap manager, suggesting a sustained period of excess return generation. We also observed that during periods of extreme market downturns, the market benchmark was in the bottom quartile of active Large Cap managers. This suggests that their portfolios' variance from the market benchmark (i.e., their Active Share) appeared to help preserve asset values in such periods. The current cycle of relative underperformance began in 2009 and has been almost four years now.

Through a regression model described in Sections Three and Four, respectively we determined and analyzed key variables that appear to drive the relative performance cycle for Large Cap managers in order to evaluate whether the recent cycle of underperformance is underpinned by structural or cyclical dynamics. Our analysis suggested that there are both cyclical and structural elements to cycles of active manager underperformance, with the most recent four plus year cycle distinguished by the dominant role of macro-economic policies. During the post financial crash period, we found that the three most harmful variables for Large Cap managers' relative performance were intra-market stock correlations (i.e., the degree of synchronicity with which individual stocks move relative to the overall market index); extreme stock performance divergence (where a handful of companies dominate the overall market's performance), and the level and change in liquidity in the financial system (a proxy for changes in monetary accommodation). This observation would suggest that normalization of these variables would foreshadow a period of active management outperformance.

Our analysis on the key variables underpinning the relative underperformance of Large Cap active managers would suggest that the observed alpha impairment over the last five years is not structural. For Small Cap and Non-US strategies, our research suggests that higher Active Share portfolios would be expected to outperform passive portfolios because of the observed structural performance advantage. For Non-US products in particular, the positive relationship between Active Share and excess return combined with the observed negative relationship between Active Share and product assets, would suggest that using smaller or entrepreneurial managers for Non-US equity allocations could be more advantageous. Actively managed Large Cap long-only products (particularly Large Core and Large Growth) should eventually revert to a period of sustained outperformance. Based on our analysis, we can think of two scenarios that could presage a cycle change. One scenario is a market downturn as in the years 2001 and 2008 (when the market benchmark was in the bottom quartile of active managers); particularly if the downturn was precipitated by a market event (such as fed tightening) as opposed to a geopolitical event. The other scenario would be normalization of stock correlations. In light of the elevated level of geopolitical instability fostered primarily by the ongoing deleveraging cycle among major developed countries, this latter scenario would be expected to be a halting, slow and possibly multi-year process.

This is the first of an ongoing series of research papers to be published by FIS Group on this topic. Future research papers will provide information on the following:

- Refine the regression analysis incorporated herein to Large Growth and Value strategies;
- Identify thresholds that might point to the inflection points in the cycle of active manager performance.

APPENDIX A: REGRESSION ANALYSIS METHODOLOGY

The inputs used for our regression analysis include:

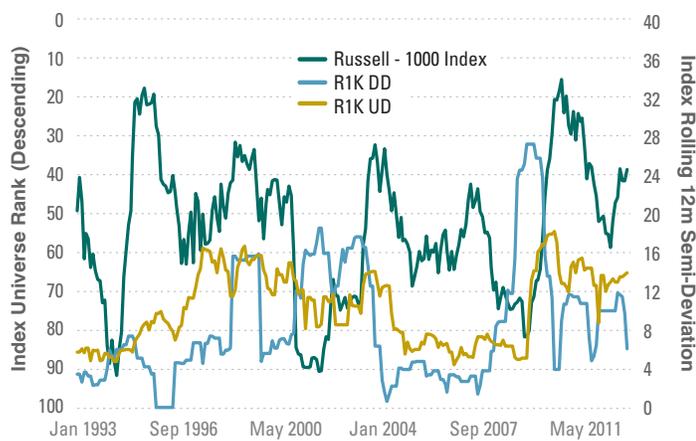
1. Russell 1000 Index Trailing 12M Return Universe Ranking (R1K Rank): this variable represents the rank of the Russell 1000 Index trailing 12M return versus a universe of active Manager Defined Large Cap Core managers from Wilshire Associates' Compass database. The manager universe includes managers that may have discontinued reporting to avoid inclusion of survivorship bias.
2. Russell 1000 Trailing 12M Upside Deviation (UD) and Downside Deviation (DD): these variables represent a measure of the upside and downside semi-deviation of the Russell 1000 Index over the trailing 12M period.
3. Russell 1000 Price Elasticity to Forward Earnings (%P vs. %E): this variable represents a measure of the average response of price to changes in forward earnings. The calculation is a rolling 12 month regression of the % change in price on the % change in forward earnings.
4. Russell 1000 Growth vs. Value Spread (G vs. V): this variable represents the spread between the trailing 12 month return of the Russell 1000 Growth Index minus the Russell 1000 Value Index.
5. FIS Group Proprietary Economic Cycle Component Indicators
 - a. Inflation Cycle (Inf. Cycle) – this proprietary indicator represents relative inflation across time and based on absolute level.
 - b. Liquidity Cycle (Liq. Cycle) – this proprietary indicator represents the amount of money flowing in the economy relative to its most recent history.
 - c. Profit Cycle (Prof Cycle) – this proprietary indicator represents the relative cyclical position of corporate profits.
6. Bank of America/Merrill Lynch High Yield Master II Option-Adjusted Spread (HY OAS): this variable represents the reported Option-Adjusted Spread for the BofA/Merrill Lynch High Yield Master II Index.
7. Russell 1000 Stock-Level Concentration Coefficient (CCoeff - Stock): this variable measures the concentration of the Russell 1000 Index at the stock level. The Concentration Coefficient is defined as the reciprocal of the sum of the squares of the weights of the holdings in a portfolio. This expresses portfolio concentration as the equivalent number of equal-weighted holdings using each individual stock's weight as the basic input.
8. Russell 1000 Sector-Level Concentration Coefficient (CCoeff - Sector): this variable measures the concentration of the Russell 1000 Index at the GICS sector level. The Concentration Coefficient is defined as the reciprocal of the sum of the squares of the weights of the holdings in a portfolio. This expresses portfolio concentration as the equivalent number of equal-weighted sectors using each individual GICS sector's weight as the basic input.
9. Russell 1000 Big minus Small Trailing 12M Spread (Big vs. Small): this variable represents the spread between the trailing 12 month return of the top quintile and the bottom quintile of companies in the Russell 1000 Index based on market cap.
10. Russell 1000 Hi Debt minus Low Debt Trailing 12M Spread (Hi vs. Lo): this variable represents the spread between the trailing 12 month return of the top quintile of companies in the Russell 1000 Index based on debt to capital and the bottom quintile.
11. Russell 1000 Top 5 minus Bottom 5 Trailing 12M Spread (Top5 vs. Bott5): this variable represents the spread between the trailing 12 month return of the top 5 and the bottom 5 performing stocks in the Russell 1000 Index.
12. Russell 1000 Profit Cycle Indicator (related to 5.c): this variable borrows the methodology for the Profit Cycle Indicator and applies it to the Russell 1000 Index specifically.
13. Russell 1000 Median Market Capitalization Universe Ranking: this variable represents the rank of the Russell 1000 Index median market cap versus the median market capitalization of a universe of active managers from Wilshire Associates. The manager universe includes managers that may have discontinued reporting to avoid inclusion of survivorship bias.
14. Russell 1000 Top 2 Sectors minus Bottom 2 Sectors Trailing 12M Spread (Top2 Spread): this variable represents the spread between the trailing 12 month return of the top two minus the bottom two performing GICS sectors in the Russell 1000 Index.
15. Russell 1000 Trailing 12M D1 Return Turnover Coefficient (Turnover): this variable represents the monthly turnover of the top decile of stocks in the Russell 1000 Index using the trailing 12M return as the relevant metric.

16. Large Cap Correlations (measured monthly) (Corr.): this variable represents a measure of the trailing 12 month correlation between the stocks in the Russell 1000 Index. It is calculated using the daily weights and logarithmic returns of Russell 1000 constituents for the period ranging from December 1998 through September 2012. Prior to that, the calculation is based on an index of 77 Russell 1000 companies with trading histories dating back to July 1980. This index is calculated by equal-weighting the 9 represented GICS sectors and then equal-weighting the stocks within each sector.
17. US Economic Policy Uncertainty Index®: From Economic Policy Uncertainty. This variable is designed to measure policy-related economic uncertainty. The index is constructed by combining three components. One component quantifies newspaper coverage of policy-related economic uncertainty. A second component reflects the number of federal tax code provisions set to expire in future years. The third component uses disagreement among economic forecasters as a proxy for uncertainty.

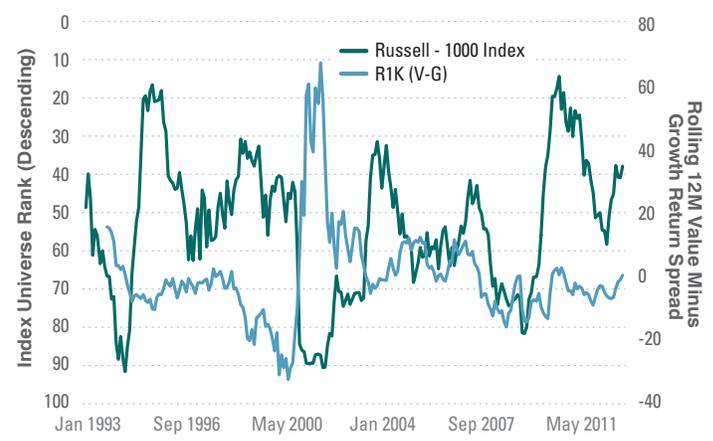
VARIABLE SELECTION

In developing our model, we first assessed each variable visually along with measuring its correlation with the R1K Rank. The graphs below represent our observations of each variable versus the R1K Rank:

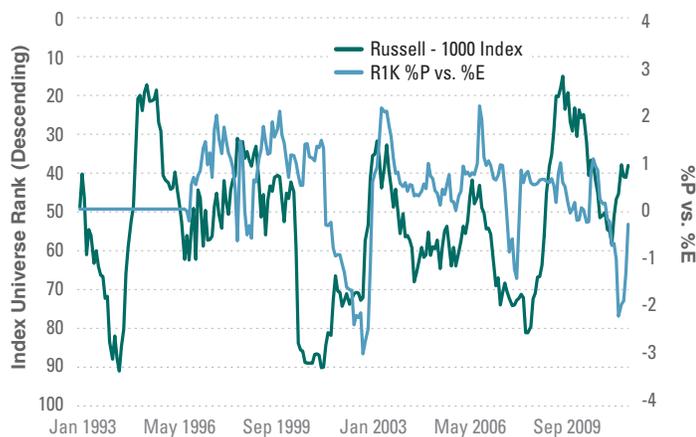
R1K Semi-Deviation



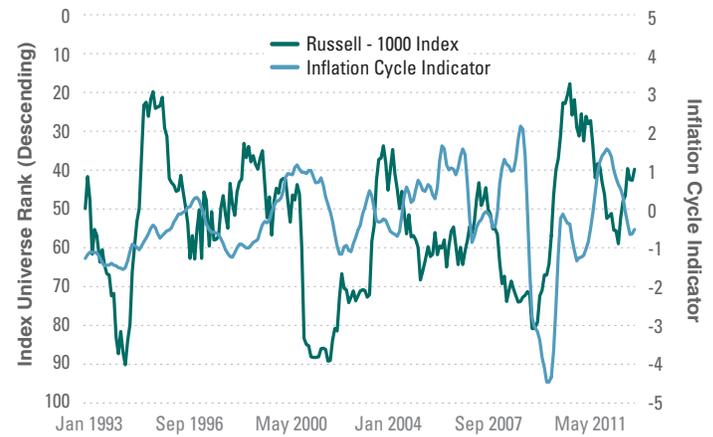
Russell 1000 Growth vs. Value



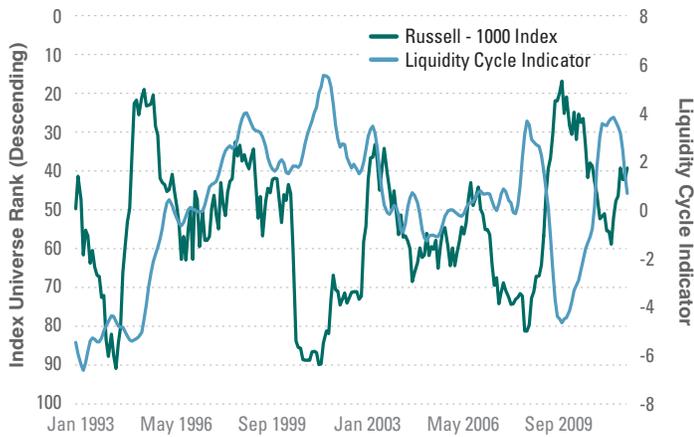
Price vs. Earnings Elasticity



FIS Group Inflation Cycle Indicator



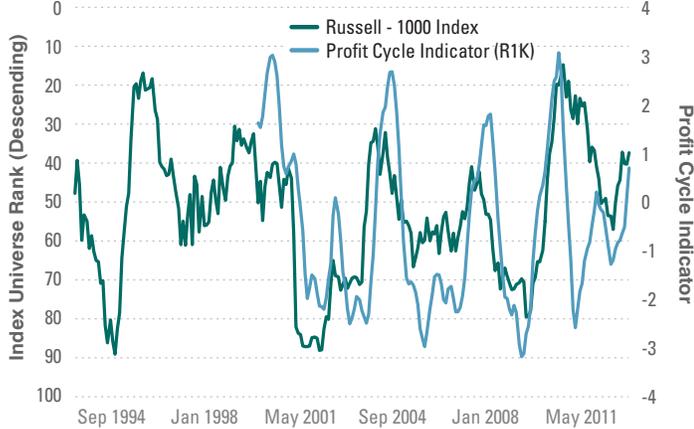
FIS Group Liquidity Cycle Indicator



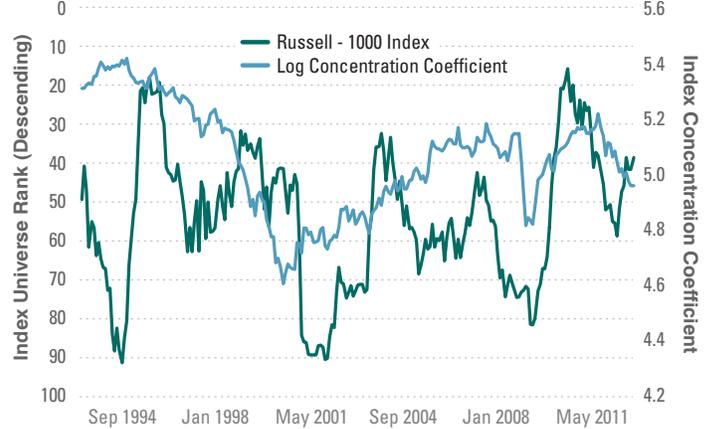
High Yield OAS



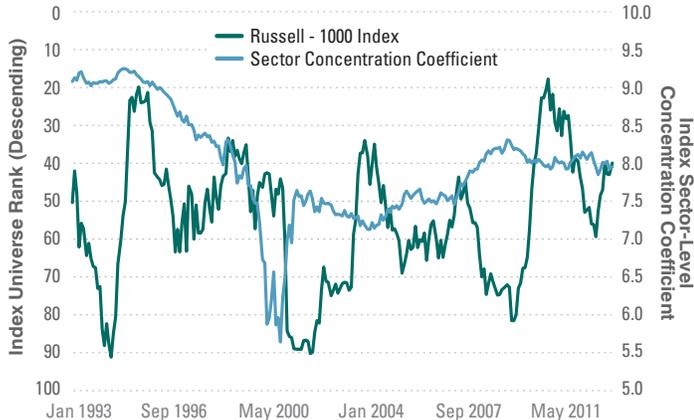
FIS Group Profit Cycle Indicator



Concentration Coefficient (Stock Level)



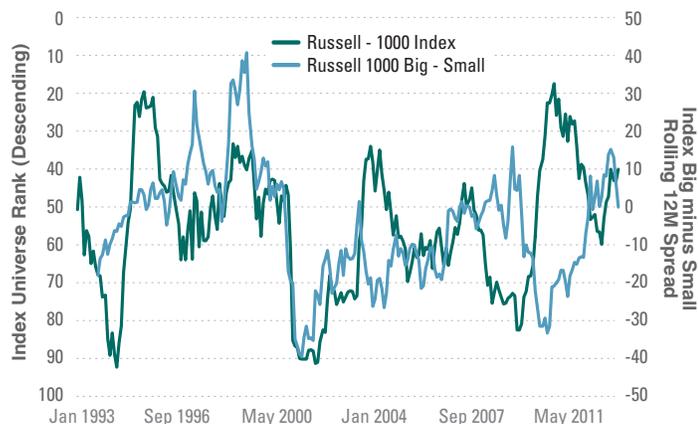
Concentration Coefficient (Sector Level)



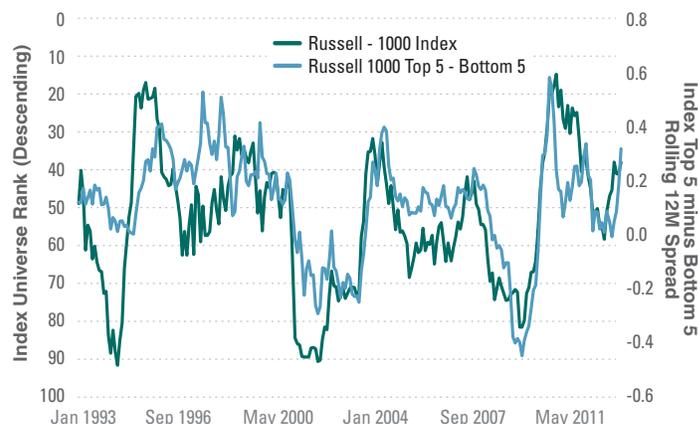
High Debt vs. Low Debt Performance Spread



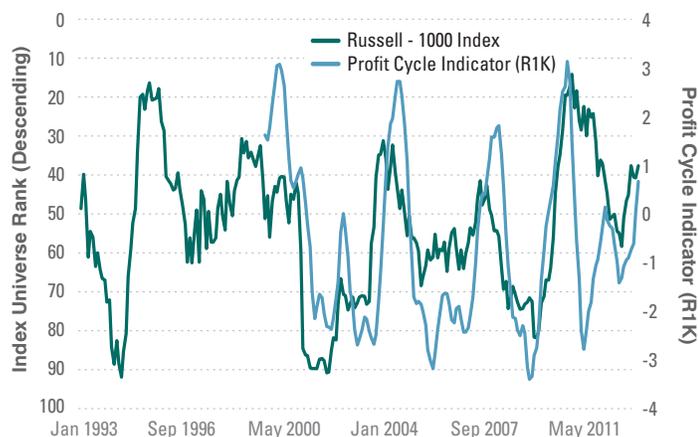
Big vs. Small Cap Performance Spread



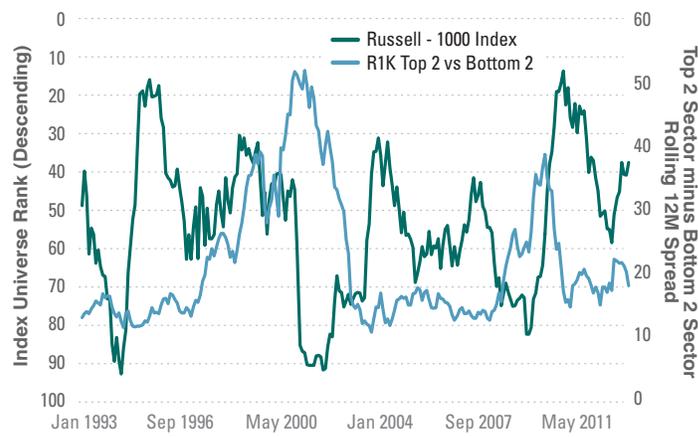
Top 5 vs. Bottom 5 Stock Spread



Russell 1K Profit Cycle



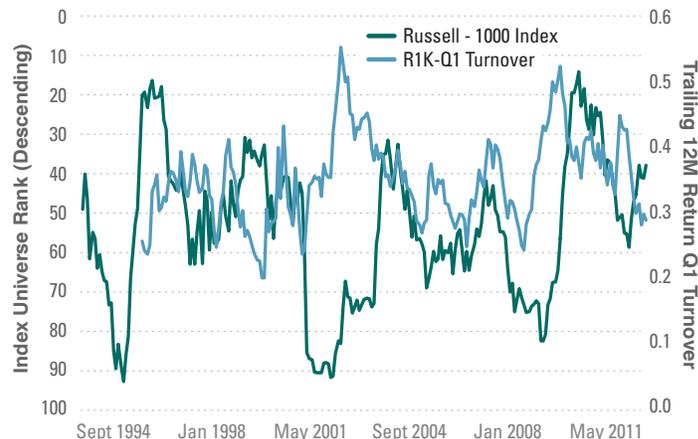
Top 2 vs. Bottom 2 Sector Performance Spread



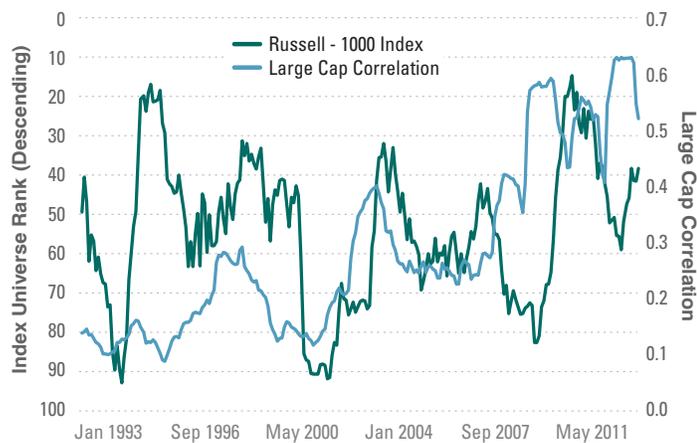
Russell 1K Median Market Cap Universe Rank



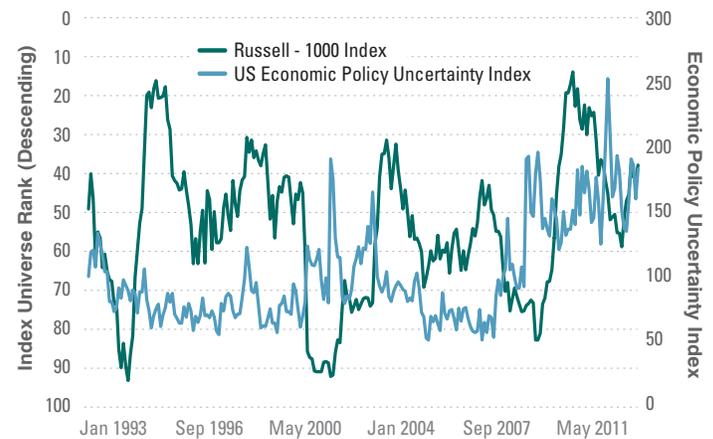
Russell 1K Top Quintile Stock Turnover



Large Cap Correlation Indicator



US Economic Policy Uncertainty Index®



Many of the variables appeared to have a relationship with the universe-relative ranking of the index's trailing 12 month performance. We further analyzed the relationships by measuring the strength of the cross correlation between the relevant variable and index universe rank. We selected those variables that had statistically significant levels of cross-correlation with the index on a coincident or leading basis. It was our view that this set of variables had the highest probability of contributing to a statistically significant model with a high degree of explanatory capability.

Our final list of input variables is as follows:

1. VAR1 - FIS Group Proprietary Liquidity Cycle Indicator
2. VAR2 - Large Cap Correlation (measured monthly)
3. VAR3 - US Economic Policy Uncertainty Index®
4. VAR4 - 1000 Profit Cycle Indicator
5. VAR5 - 1000 Big minus Small Trailing 12M Spread
6. VAR6 - 1000 Top 5 minus Bottom 5 Trailing 12M Spread
7. VAR7 - Russell 1000 Trailing 12M Top Decile Return Turnover Coefficient
8. VAR8 - Russell 1000 Top 2 Sectors minus Bottom 2 Sectors Trailing 12M Spread (Top2 Spread)
9. VAR9 - Russell 1000 Price Elasticity to Earnings

MODELING APPROACH

With the independent variables selected, we proceeded to develop our model. We used monthly data spanning from December 1993 to the end of the third quarter of 2012, in doing so, we faced a particular challenge that we needed to address. Each of the variables we analyzed had strong trends that were not random as is the case with daily returns to equity indices. As a result, the method of modeling relationships between the variables needed to account for this fact. The simplest models to explain are linear regression models; however, when variables are not random the results of linear regression models cannot be relied upon. The exception to this rule occurs when the variables are cointegrated. Cointegration, simply put, suggests that there is a long-term relationship between the variables that they will return to when there are short-term deviations. A research paper written by Hashem Pesaran was instructive in our analysis.¹⁸

Step 1: Simple Linear Regressions

Based on the premise that variables that are likely to be cointegrated and probably also exhibit a high degree of linear dependence, we performed simple regressions of our target, the relative universe ranking of the Russell 1000 Index, on each of the 9 input variables we selected for inclusion in our model development process. The output on the next page shows the results of this initial analysis:

Variable Name	Intercept	Beta	P-Value
VAR 1	53.41	0.16	0.04%
VAR 2	63.82	(0.35)	0.00%
VAR 3	59.37	(0.05)	16.51%
VAR 4	54.50	(0.32)	0.66%
VAR 5	51.56	(0.28)	0.10%
VAR 6	58.46	(0.45)	0.00%
VAR 7	31.83	0.60	0.15%
VAR 8	42.98	0.49	0.01%
VAR 9	54.21	0.12	50.89%

With the exception of the Economic Policy Uncertainty Index and the Price Elasticity to Forward Earnings, each of the variables was statistically significant within a 99% confidence interval. These results were encouraging and provided the basis for the next step in our process.

Step 2: Co-integration Analysis & Regression Modeling

First, we tested to ensure that each variable was integrated of order 1, which simply means that we confirmed that if we measured the change in the variables they would have a ‘constant’ mean and variance. We then performed a co-integration test to determine whether the variables and R1K rank were co-integrated. Our results indicated that the variables were indeed co-integrated so we performed a regression analysis. In performing the regression analysis we incorporated a moving average error term to account for the induced serial correlation caused by the use of overlapping periods as independent variables. The results of analysis are listed below:

One can observe that the significance level of VAR8 (Top 2 Sectors minus the Bottom 2 Sectors) is not statistically significant.

Variable Name	Intercept	Beta	T-Stat
Intercept	97.73		9.88
VAR 1		0.39	6.51
VAR 2		(0.40)	(5.81)
VAR 5		(0.45)	(5.38)
VAR 6		(0.33)	(4.55)
VAR 7		(0.95)	(4.30)
VAR 8		(0.07)	(0.50)
Adj R ²	90.28%		

While the model is statistically significant and provides insight into the overall dynamics of the active premium over time, the primary question we are trying to address is whether or not the premium to active management has in some way been impaired. In particular, have the events of the Financial Crisis of 2008 shifted the market dynamics in a meaningful way.

In exploring this question, we analyzed a “Post-Crisis” period beginning in January 2007 and inclusive of the remaining data points (through December 2012). Using the methodology outlined previously, we identified a cointegrated set of variables and the associated model whose outputs are provided below:

Variable Name	Intercept	Beta	T-Stat
Intercept	135.86		8.99
VAR 1		(0.59)	(4.72)
VAR 2		(3.81)	(7.42)
VAR 3		1.01	7.45
VAR 4		1.24	8.14
VAR 5		(1.13)	(10.01)
VAR 6		(0.54)	(1.86)
Adj R ²	94.51%		