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DYNAMIC CONTEXTUAL ALPHA: A Differentiated Approach To Quantitative Enhanced Indexing

EXECUTIVE SUMMARY

From the 1980s onward, many investors began to diversify their US equity exposure (previously either indexed or actively managed) with allocations to quantitative enhanced index funds. While active management thrives on finding alpha in exceptional situations, quantitative management is able to add value in a “law-of-large-numbers” setting.

Quantitative enhanced indexing targets greater alpha consistency, while active management offers the potential of higher excess returns. By construction, active and quantitative alphas are very different, and over time they effectively diversify each other.

Since the liquidity crunch of August 2007, many quantitative funds have underperformed, leaving investors to consider whether to remain with their existing enhanced managers in the hopes of a comeback, or exit enhanced indexing completely.

We believe there is another solution that both preserves the benefits of quantitative alpha, while addressing the recent alpha slump of traditional enhanced indexers. Since 2000, a unique breed of quantitative managers who utilize Dynamic Contextual Alpha models has been outperforming the traditional quantitative group, simultaneously preserving diversifying correlations with active managers. These models recognize that ranking companies within fundamentally similar groups of stocks is more effective than ranking the entire universe or heterogeneous sectors.

Rather than waiting for the older architectures of enhanced indexing to bounce back, investors may be better served by investigating this more intuitive and adaptive form of quantitative alpha. This paper explores the evolution of quantitative enhanced indexing and demonstrates why this innovative architecture, Dynamic Contextual Alpha, continues to outperform.

Quantitative Enhanced Indexing

Ever since the concept of diversification was formalized by Harry Markowitz at Yale University¹ in the 1950s, the asset management industry has pursued a continuous quest for new and diverse ideas, asset classes and fund managers. Since the mid-1980s and the rise of computer technology, quantitative enhanced indexing emerged as a new class of equity management, providing investors with desired exposure to a given market beta with an opportunity to add alpha above the index in a risk-controlled way.

Due to low correlations with traditional active managers (an average pair-wise correlation of 10%),² quantitative enhanced index funds have generated a diversifying source of alpha that has earned the strategy a prominent allocation in investors' portfolios. Over the past decade, the category has grown both in terms of AUM and the number of offerings (**Figure 1**).

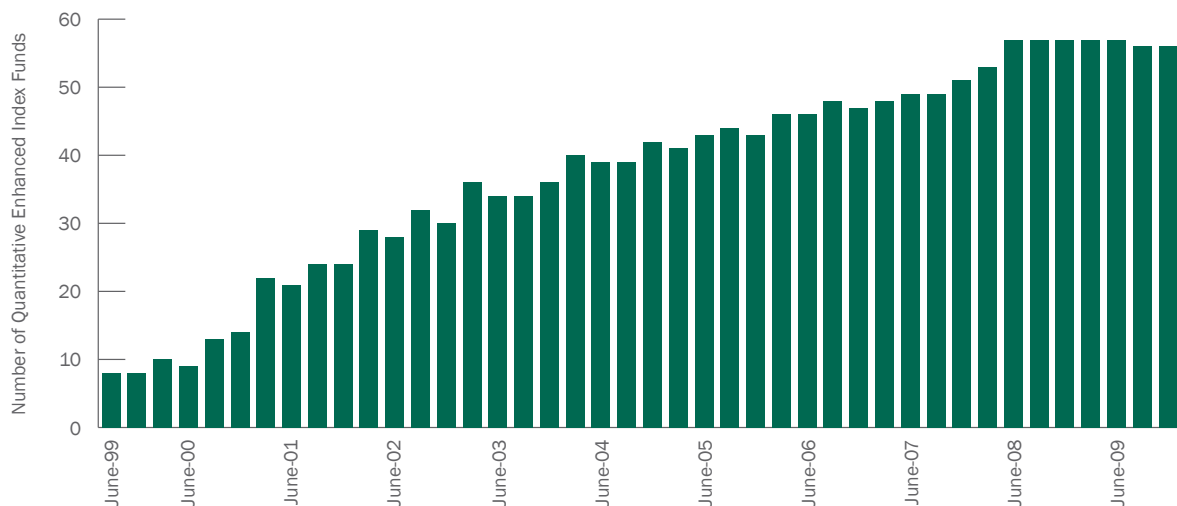
Quantitative managers were able to draw the majority of enhanced index assets because they historically generated the most consistent information ratios. This was due to their inherent ability to analyze large numbers of companies needed to create portfolios with low levels of tracking error. However, the meltdown in certain quantitative strategies during the liquidity

crisis of 2007 — and subsequent underperformance of quantitative funds — has focused attention on the “overcrowding” of these traditional quantitative approaches.

We believe an alternative solution both preserves the long-run diversification and consistency benefits of quantitative alpha and addresses the recent alpha slump. Since 2000, by utilizing an innovative approach in construction of their models, a small group of quantitative managers has been outperforming the traditional quantitative funds, while preserving the diversifying correlations with active managers. Instead of waiting for older models of enhanced indexing to bounce back, investors may be better served investigating this more flexible form of quantitative alpha.

This differentiated approach, called Dynamic Contextual Alpha,³ recognizes that quantitative factors work best when they are used to distinguish investment opportunities between fundamentally similar firms, rather than structurally different ones. In order to maximize the effectiveness of factors, stocks should first be assigned into groups of fundamentally similar firms, and then ranked on specific quantitative metrics that are most effective in each group.

FIGURE 1 Growth in Number of Quantitative Enhanced Index Funds



Source: eVestment Alliance data for Enhanced S&P 500 Index Equity Universe as of 30 September, 2009.

1 Markowitz, Harry, “Portfolio Selection: Efficient Diversification of Investments.” New York: John Wiley & Sons, 1959.

2 eVestment Alliance data for Enhanced S&P 500 Index Equity and Large Cap Core Equity Universes as of 30 September, 2009.

3 Sorensen, Eric H., Hua, Ronald and Qian, Edward E., “Contextual Fundamentals, Models, and Active Management.” February 2005.

Evolution of Quantitative Models

The original quantitative models of the late 1980s through early 1990s ranked stocks on the simple value, momentum and earnings revisions factors that were sufficient to outperform the benchmark.

In the 1990s, Grinold and Kahn published an influential book⁴ that showed a portfolio's information ratio can be decomposed into the *information coefficient* of each factor, as well as the *breadth* of factors. (Information coefficient is the degree to which any given factor ranking predicts future stock returns, and breadth is the number of unique factor rankings used in the portfolio.)

In search of more breadth, managers enhanced definitions of existing quantitative themes and implemented additional ones. For example, instead of using just price-to-book and price-to-earnings as factors that capture the value theme, managers added price-to-cash flow and enterprise value-to-EBITDA metrics.

Following a wave of academic publications in the late 1990s,⁵ earnings quality and profitability themes were added to this mix of criteria, providing additional breadth to the models.

On a parallel track, fueled by advances in risk management, sector models began to evolve. In addition to ranking all the stocks in the universe based on a set of factors, models began ranking stocks per sector and then combining the universe-wide and sector-neutral ranks. Managers recognized that different factors have varying effectiveness, depending on the sector of a particular company. As a result, factors began to be customized based on a company's sector membership.

“The main idea behind a Dynamic Contextual model is to rank stocks within groups of securities with similar attributes and only apply factors relevant to the group.”

The primary benefit of sector models is the improvement in breadth because of the increased number of independent rankings. For example, a factor like price-to-book can act differently when used in the Financials sector, versus the Energy sector. Additionally, if it is predictive of future returns in both sectors, using two sector-neutral price-to-book scores will produce a more stable overall return than ranking all the Energy and Financial stocks together on that one metric.

A variety of sector-specific metrics can also further increase the diversification of alpha sources. Traditional quantitative enhanced indexers today use some combination of ranking stocks within the overall universe, as well as within their corresponding sectors.

Even though sector models represent an important step in the right direction, they have two significant drawbacks. First, sector groupings miss the fact that just because any two companies derive their revenue from a similar economic activity, their business models, corporate strategies and growth trajectories can be radically different. As a result, a fast-growing innovative technology company might be more similar to a fast-growing health care company than to another technology company with declining sales growth.

Second, sector groupings are static and miss important changes that occur in a company's fundamentals over time. Even though Standard & Poor's (S&P) occasionally recategorizes sector memberships, these overall assignments rarely change over a typical investment horizon of one to two years.

As an outcome, typical factors can become less relevant and effective as company fundamentals change over time. So while the breadth component of information ratio is enhanced by sector models, the predictive element of the model diminishes over time, leading to lower information ratios.

Dynamic Contextual Alpha

Since the early 2000s, Dynamic Contextual Alpha has emerged as a different approach to ranking stocks. This concept was discussed by Richard Sloan in 2001⁵ and later formalized by Sorenson, Hua and Qian in 2005.⁶ The main idea behind a Dynamic Contextual model is to rank stocks within groups of securities with similar attributes and only apply factors relevant to the group.

These groups or contexts are updated periodically and consist of stocks that share some common fundamental characteristics. As each company's characteristics evolve with time, so does its assignment to a specific group. One particular approach to categorize securities is by the stage of the company's life cycle, which can range from early start-up phase, to fast growth and slow mature growth states.

4 Grinold, R., Kahn, R, "Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Controlling for Risk." McGraw-Hill, October 1999.

5 Sloan, Richard G., "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings?" The Accounting Review, Vol. 71, No. 3, Spring 1996.

6 Sorensen, Eric H., Hua, Ronald and Qian, Edward E., "Contextual Fundamentals, Models, and Active Management." February 2005.

Another way to group stocks into contexts is through their exposures to a common set of risk factors like growth, value and earnings stability. A well-defined context, within which each company is analyzed and ranked, significantly improves information ratios by both improving model breadth and information coefficient.

Dynamic Contextual Alpha models improve upon sector models in two ways. First, Dynamic Contextual models recognize that grouping companies based on common fundamentals will lead to more meaningful rankings, as factors will be ranking similar types of stocks against each other, generating “apples to apples” comparisons.

For example, a fast-growing technology company like Google has much in common with — and should be compared to — a fast-growing health care company like Amgen. Both are at similar stages of their individual life cycles, and, therefore, are dealing with similar business issues (investing for growth), versus the mature technology and health care companies like Xerox or Tenet Healthcare that need to focus on maintaining or improving profitability. Hence, factors that identify improvements in growth should be used to rank the fast-growth stocks, while factors that capture improving profitability should be used to evaluate mature stocks.

Second, contextual models improve upon sector models because of the more dynamic nature of contextual groupings, which allow companies to migrate from one group to another as the firms’ individual fundamentals change. As a result, factors that are used to rank stocks

adapt to a company’s characteristics, which safeguards the model against missing major changes in both company-specific and sector-wide fundamentals.

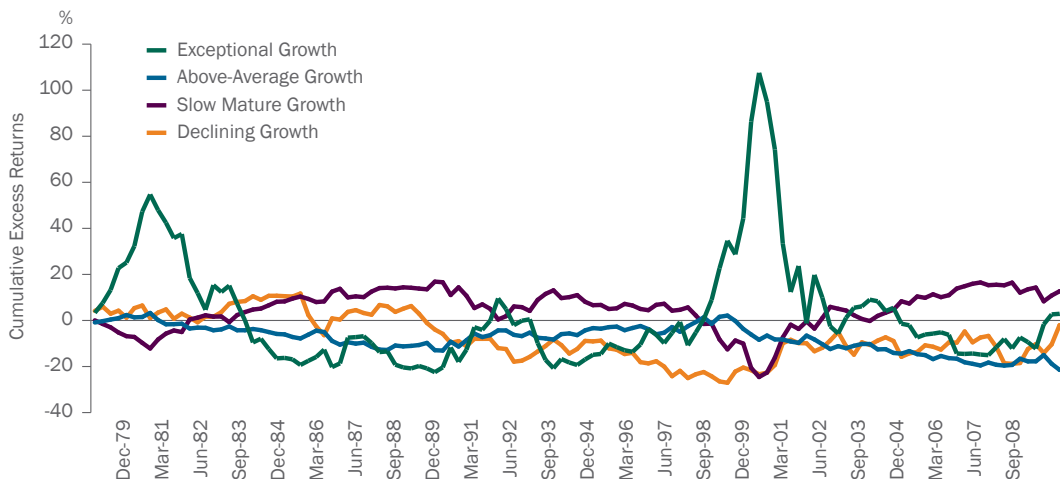
Empirical Results

We now illustrate two specific benefits of contextual modeling based on a “flavor” of context that categorizes stocks based on their stage in the life cycle. First, we demonstrate that customizing factors that are logically suited to a company’s stage of growth, and then ranking on those factors within a life-cycle context, boosts predictive effectiveness of these factors.

Second, we use Energy stocks to show that many of them changed their growth characteristics through time from fast growth in the 1970s, to slower mature growth in the 1980s and 1990s, and then again to above-average growth in the 2000s. As a result, the effectiveness of classic growth and value factors on these Energy stocks depends on the growth state of the underlying sector.

Putting it all together, we demonstrate that a model comprised of a combination of typical quantitative factors achieves a 100% increase in the information ratio when applied in the contextual way, versus the traditional way. Finally, we document a similar improvement in the realized information ratios for a group of managers that utilizes dynamic contextual models, versus the more traditional, enhanced indexers.

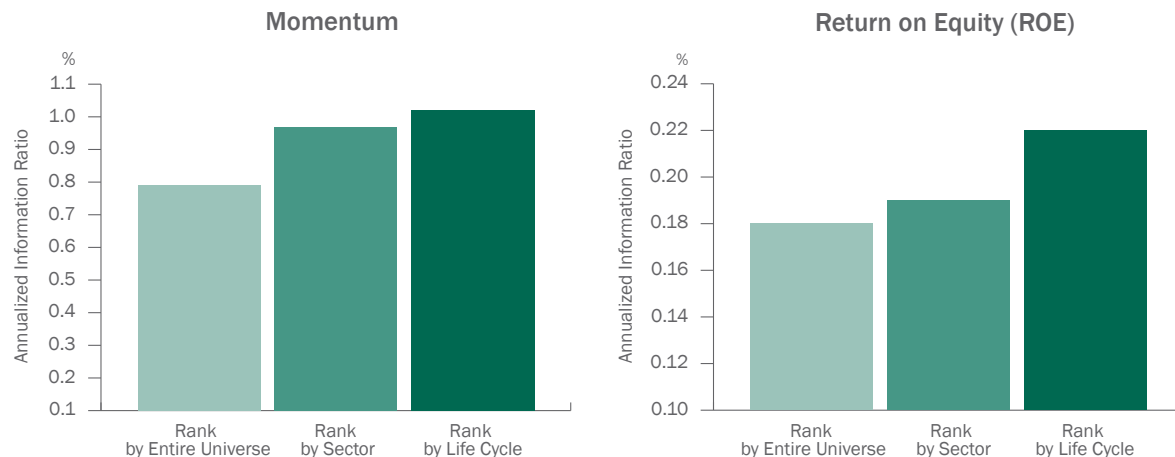
FIGURE 2 Distinct Patterns of Cumulative Excess Returns of Life-Cycle Categories



Source: IDC Pricing, Compustat Fundamental Data, IBES Estimates, as of 30 September, 2009.

FIGURE 3

Information Ratio of Top Minus Bottom Quintile Spread



Source: IDC Pricing, Compustat Fundamental Data, IBES Estimates, as of 30 September, 2009.

Defining Dynamic Context

We categorize all large-cap U.S. stocks into four distinct life-cycle groups: Exceptional Growth; Above-Average Growth (although not Exceptional); Slow Mature Growth (although not Declining); and Declining Growth.

“Any company’s stage of growth is dynamic, and, so too, must be its inclusion into a given category and the selection of factors applied to evaluate its attractiveness.”

We use the largest 1,000 US companies by market cap, and we compute a growth rate score for each stock by combining both historical and consensus forward-looking growth rates. We then split the universe based on this growth score into the aforementioned four life-cycle groups. Exceptional Growth and Declining Growth each constitute about 10% of the universe, with the rest split equally between Above-Average Growth and Slow Mature Growth categories. To allow companies to change growth rates over time, we recategorize each stock into one of four growth categories quarterly, and then plot the capitalization-weighted excess returns of each group over the past 30 years, as seen in **Figure 2**.

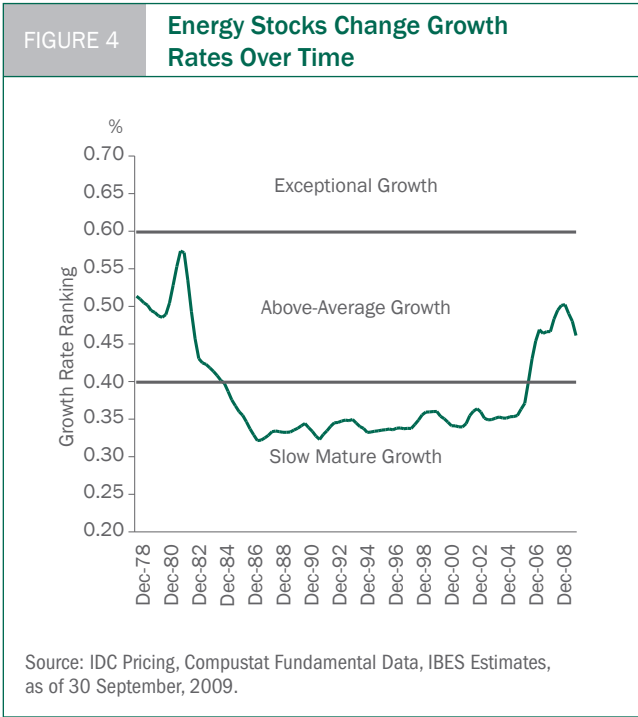
The results clearly indicate that these groups of stocks behave differently over time, but no single group outperforms the others in the long run.

The business issues faced by each grouping of stocks are distinct from the others and need to be analyzed accordingly. Any company’s stage of growth is dynamic, and so too must be its inclusion into a given category and the selection of factors applied to evaluate its attractiveness.

Benefit 1: Ranking Fundamentally Similar Companies Boosts Effectiveness of Typical Factors

Two commonly used growth factors demonstrate the first benefit of a properly defined context. Using 11-month Price Momentum and Return on Equity (ROE), we separately rank first the entire universe, then each sector, and finally each life-cycle grouping, as defined earlier, into quintiles (i.e., rank 1–5).

We then compute capitalization-weighted excess returns of each quintile for each of the three ranking methodologies. The annual information ratio of the Top Quintile minus Bottom Quintile return using the life-cycle rankings increases by 25% and 22% for Momentum and ROE respectively, compared to rankings across the entire universe (**Figure 3**). This occurs because comparing companies with similar characteristics is more powerful than comparing very different companies across the universe — and even across sectors.



the early 1980s, following the oil boom of the late 1970s, Energy stocks still had above-average growth scores, and, according to our simple categorization rule, were classified as “Above-Average Growth” stocks. Yet, they quickly began to mature, and by the mid-1980s until the recent oil boom, Energy stocks grew slower than average and were recategorized as “Slow Mature Growth.” The latest oil boom pushed Energy companies’ growth rates up, recategorizing them once again as “Above-Average Growth” (Figure 4).

“...the same factors applied to the same group of stocks can produce very different results, depending on their underlying fundamentals at a particular point in time.”

Benefit 2: Dynamic Nature of Contextual Groups — An Average Energy Stock Example

To demonstrate the dynamic benefit of contextual groups, we could use a variety of individual stocks or groups of stocks that experienced significant changes in growth characteristics and resulting characterizations over time. Energy stocks are one clear example, but since the life-cycle categorizations are done on stock-level data, the results can be generalized to any other group of stocks. The historical variability of the growth-rate score for an average Energy sector stock is shown in Figure 4. During

Ignoring the evolution of a firm’s fundamentals leads to frequent misapplication of common factors. For example, a typical growth factor, such as ROE, and a typical value factor, such as price-to-book, logically and empirically exhibit very different effectiveness under the two growth states of the Energy stocks.

As outlined in Figure 5, information ratio of the price-to-book factor applied to the Energy sector is 50% higher when these stocks are in the Slow Growth state, as opposed to the Above-Average Growth state.

The opposite can be seen in the ROE factor, which is effective when Energy stocks are in the Above-Average Growth state and is ineffective during the Slow-Growth

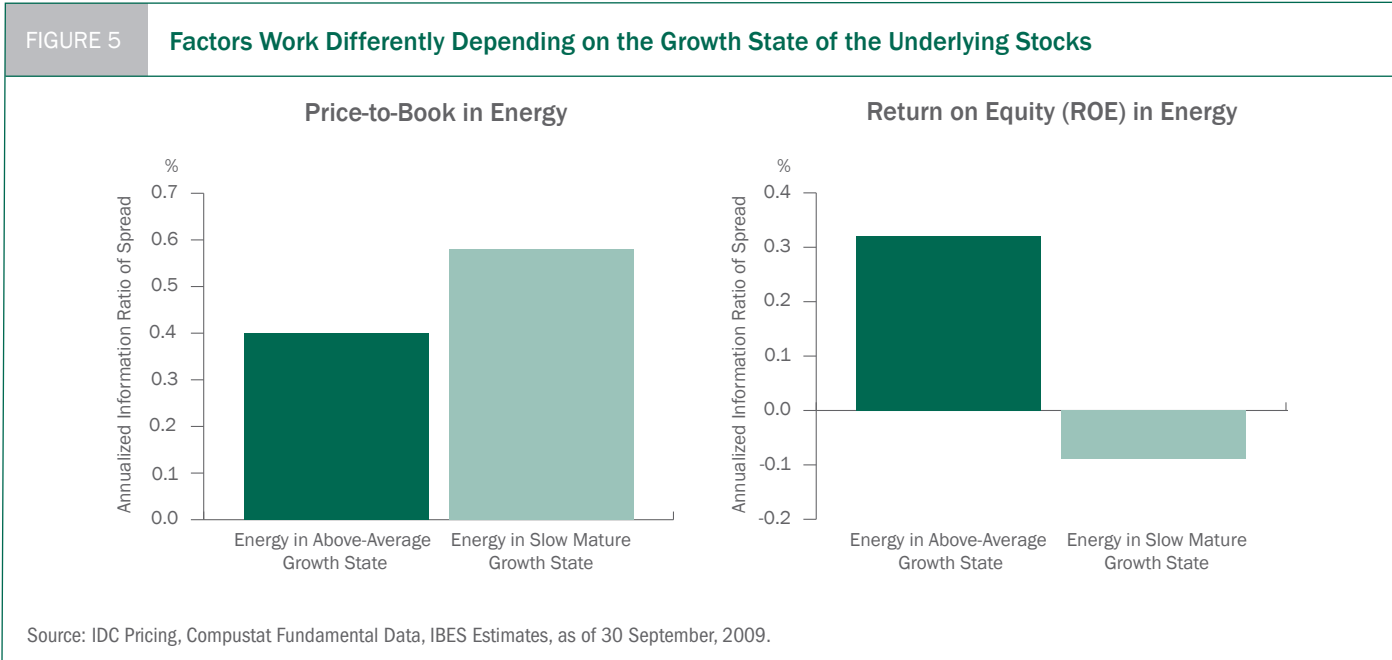
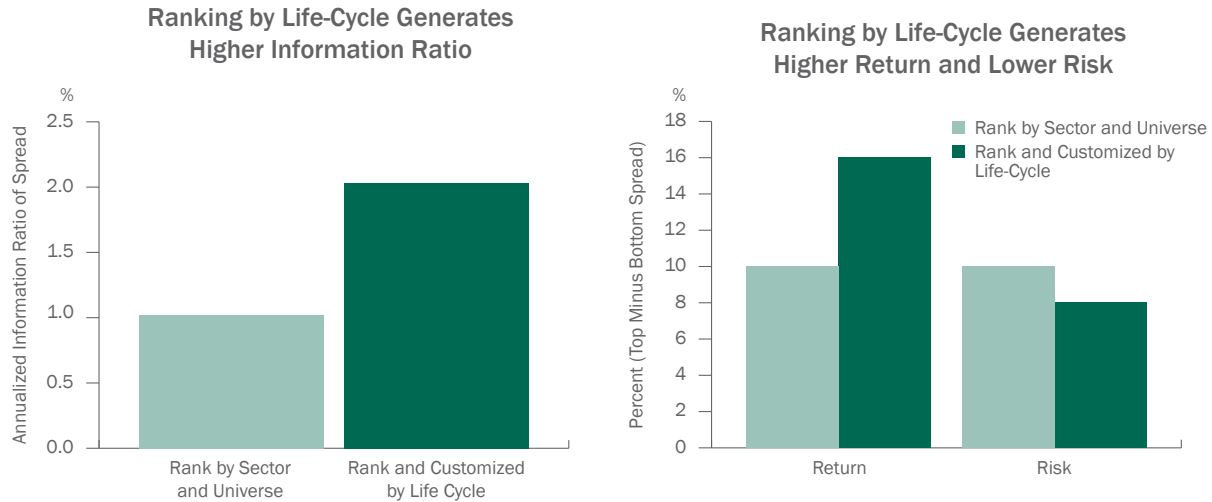


FIGURE 6

Factors Are Most Effective When Applied and Customized by Life Cycle



Source: IDC Pricing, Compustat Fundamental Data, IBES Estimates, as of 30 September, 2009.

state. This demonstrates the benefit of the dynamic nature of these contextual groups because the same factors applied to the same group of stocks can produce very different results, depending on their underlying fundamentals at a particular point in time.

Putting It All Together

From January 1979 to September 2009, using a large set of common quantitative factors from Value, Revisions, and Quality themes, we have created two versions of a composite score for the largest 1,000 US stocks (Figure 6). Using the full set of factors, Version 1 ranks companies within the entire universe and within each sector and then combines the two ranks. Version 2 ranks companies within their life-cycle groups and uses only the fundamentally meaningful factors in each of the four categories.

“...managers utilizing the contextual approach consistently outperformed those who did not.”

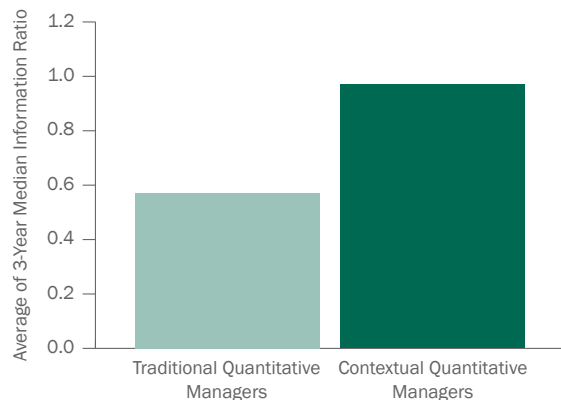
The result is a 100% increase in the information ratio of Version 2 over Version 1. When factors are logically customized to each stage of growth, and each stock’s stage of growth is dynamic, model returns are higher – and the risk is lower – than when all factors are applied to all stocks equally or by sector. This seems to be the most likely reason why the group of managers utilizing the architecture of Dynamic Contextual Alpha continues to outperform.

Dynamic Contextual Managers Versus Traditional Quantitative Managers

In comparing the realized performance of Dynamic Contextual Alpha managers, versus their more traditional, older architecture peers, we use eVestment Alliance data for the S&P 500 Enhanced Index Universe and cull it down to only quantitative managers. We label those that clearly describe some concept of unique stock categorization as “Contextual,” and all others “Traditional.” Figure 7 shows the average three-year rolling median information ratios for both groups. Over the past decade, managers utilizing the contextual approach consistently outperformed those who did not.

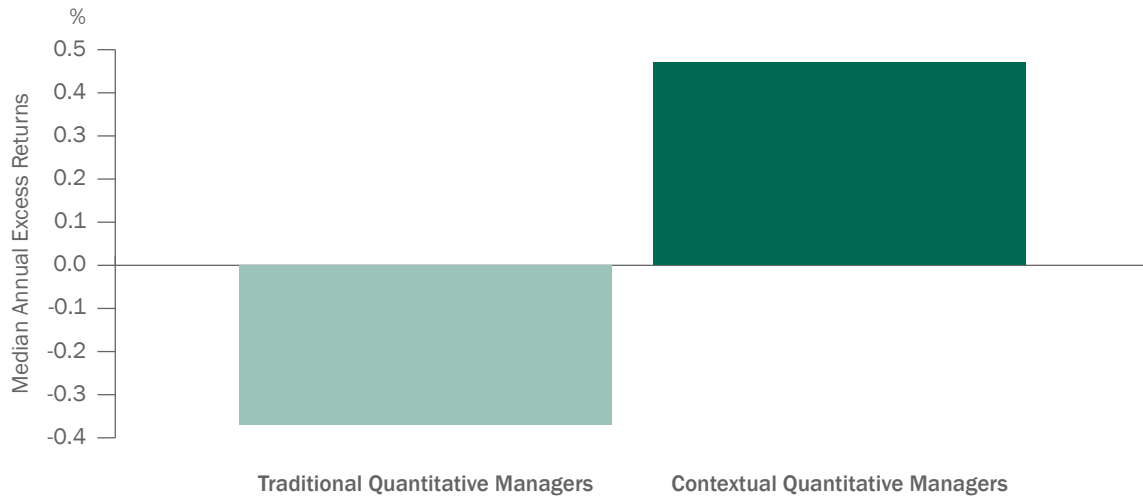
FIGURE 7

Dec ‘99–Sep ‘09: Contextual Managers Delivered Higher Information Ratios



Source: eVestment Alliance data for Enhanced S&P 500 Index Equity Universe as of 30 September, 2009.

FIGURE 8

Contextual Alpha Managers Held Up Better in the “Tough For Quants” 2007

Source: eVestment Alliance data for Enhanced S&P 500 Index Equity Universe as of 30 September, 2009.

Not only did contextual managers perform better over the long run, but more importantly, during the severe liquidity crunch of 2007, they consistently outperformed traditional quantitative managers. Median contextual manager outperformed median traditional manager by about 84 basis points in 2007, which constituted a significant portion of the targeted level of alpha for enhanced indices (**Figure 8**).

Conclusion

While active management thrives on finding alpha in exceptional situations, quantitative management adds value in a “law-of-large-numbers” environment. These types of managers are thus inherently complementary because of the low correlations with each other. In our view, a successful form of quantitative alpha continues to merit allocations in well-diversified portfolios.

Recent underperformance of traditional quantitative enhanced indexing can be addressed by migrating to the less-crowded architecture of Dynamic Contextual Alpha. This approach not only continues to perform well, but also preserves the benefits of diversifying the source of alpha between active and quantitative.

Dynamic Contextual Alpha models recognize that ranking companies within dynamic groups of stocks with similar characteristics is more meaningful than ranking across all the stocks in the universe or in sectors. As a result, quantitative enhanced indexers that utilize these models delivered higher information ratios than traditional quantitative funds both historically and recently, providing a more effective way to gain exposure to quantitative alpha. ■

Breadth: The number of unique factors or distinct signals that are used to predict stock/portfolio returns.

Dynamic Contextual Alpha Model: “Dynamic” refers to the fact that assignment of each security to a particular context changes over time, driven by changes in company attributes. “Contexts” are groups of securities with similar attributes.

Factor Exposure: Sensitivity of a stock or portfolio return to a given attribute, called a factor.

Information Coefficient: The correlation between forecasted and realized returns for a set of securities.

Information Ratio: A measure of risk-adjusted active return of a stock or portfolio. Information Ratio is defined as active return divided by tracking error.

Law-of-Large Numbers: In a portfolio setting, when a large number of small investments delivers alpha over time.

Quantitative Factor: A variable or an attribute of a stock or a group of stocks. “Alpha” factors have the ability to predict security returns. “Risk” factors have the ability to predict security risk.

Quantitative Enhanced Indexing: Enhanced Indexing provides exposure to a particular index beta and aims to deliver consistent alpha above that index, given a certain level of tracking error. The stock selection engine in quantitative enhanced indexing is a model that combines a variety of alpha factors.

Liquidity Crunch of 2007: A period of rapid deleveraging by multi-strategy hedge funds, which resulted in extreme negative returns for many quantitative factors. This process was triggered by margin calls in the structured fixed income portions of multi-strategy portfolios, which forced the sale of the more liquid quantitative equity positions.

Risk Management: Managing and monitoring a portfolio to avoid unintended risks and exposures, as well as to adhere to targeted tracking error.

Sector-Neutral: Refers to the fact that ranking securities within their corresponding sectors based on a given factor neutralizes any sector biases that a factor might have. As a result, an equal percentage of each sector will end up final fractiles (i.e., 20% if quintiles are used).

Top Quintile Minus Bottom Quintile: A common way to measure effectiveness of a factor is to compute the return of Top (1-ranked stocks) minus Bottom (5-ranked stocks) Quintiles, which roughly approximates the return to over/underweights in the portfolio that invests in the factor.

Tracking Error: A measure of portfolio risk relative to a benchmark. The standard deviation of the difference between portfolio return and benchmark return.

BIOGRAPHIES



Mikhail Samonov, CFA, Vice President, Structured Equities Group

Mr. Samonov joined the firm in 2004 and is a Quantitative Analyst for the Structured Equities team. He is responsible for developing and enhancing the quantitative stock selection and portfolio construction platforms for global enhanced index portfolios. Mr. Samonov received a Bachelors of Science with honors in Applied Mathematics and Economics from Brown University. He also received an MBA from the Wharton School of Business MBA for Executives at the University of Pennsylvania. Mr. Samonov is a CFA charterholder.



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Ms. Ali joined the firm in 2005 and is responsible for quantitative model research, developments and enhancements for PineBridge Investments' Structured Equities products. Previously, she was a Consultant for the Financial Models Company. Ms. Ali holds degrees in Mathematics and Management from St. Francis College and University of Hyderabad, respectively, and an MS from Rensselaer Polytechnic Institute. She is pursuing a Masters in Computational Finance from Carnegie Mellon University. She has passed Level II of the CFA examination.

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