Chapter 30
EARNINGS FORECASTS AND REVISIONS, PRICE MOMENTUM, AND FUNDAMENTAL DATA: FURTHER EXPLORATIONS OF FINANCIAL ANOMALIES

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CHAPTER OUTLINE:

Abstract
Earnings forecasting data has been a consistent, and highly statistically significant, source of excess returns. This chapter discusses a composite model of earnings forecasts, revisions, and breadth, CTEF, a model of forecasted earnings acceleration, was developed in 1997 to identify mispriced stocks. Our most important result is that the forecasted earnings acceleration variable has produced statistically significant Active and Specific Returns in the Post-Global Financial Crisis Period. Simple earnings revisions and forecasted yields have not enhanced returns in the past 7-20 years, leading many financial observers to declare earnings research passé. We disagree! Moreover, earnings forecasting models complement fundamental data (earnings, book value, cash flow, sales, dividends, liquidity) and price momentum strategies in a composite model for stock selection. The composite model strategy excess returns are greater in international stocks than in U.S. stocks. The models reported in Guerard and Mark (2003) are highly statistically significant in its post-publication time period, including booms, recessions, and highly volatile market conditions.

Keywords
Portfolio theory, portfolio construction, portfolio management, earnings forecasts, earnings revisions, portfolio optimization.

30.1 INTRODUCTION
The purpose of this study is to document the effectiveness of a composite model of earnings forecasts, revisions, and breadth, CTEF, a model of forecasted earnings acceleration, developed in 1997, that has continued to produce statistically significant Active and Specific Returns in its post-publication

period. The forecasted earnings acceleration variable has produced statistically significant Active and Specific Returns in the Post-Global Financial Crisis Period. The composite model of earnings, price momentum, and fundamental data is a consistent source of alpha in the U.S. and international markets. Excess returns are greater in international stocks than in U.S. stocks. The U.S. market is more efficient than international markets. This study is composed of five sections. The model has worked in booms, recessions, and highly volatile market conditions. The first section addresses what we knew in 2002 with regard to earnings forecasting, composite modeling of earnings forecasting and fundamental variables, and what risk models were available for creating and monitoring the effectiveness of optimized portfolios. The second is a brief literature review of the fundamental variables, the earnings forecasting models, and the price momentum variables used in our composite models. The third section examines the APT and Axioma Risk Models used in the analysis of the post-Global Financial Crisis time period. The fourth section asks if a bottom-up stock picker's world has changed post-2003 or post-Global Financial Crisis periods. The fifth section presents summaries and conclusions and thoughts regarding future research and testing.

30.2 WHAT WE KNEW IN 2002: A TEST OF ANALYSTS' FORECASTS, REVISIONS, AND BREADTH

In September 2001, GlobeFlex needed to create an in-house model of earnings expectations. The office (and backup facility) of its vendor of the variables had been destroyed in the "9/11" attack. The research plan was to create an earnings-based variable with an institutional risk model. The construction of the variable was necessary because variables of analysts' forecast revisions were highly statistically associated with stock returns. The reader is referred to section 3 for a summary of the financial analysts' forecasting literature review. Stock selection utilizing analysts' forecasts, forecast revisions and a breadth (direction of forecast revisions) variable integrated with an institutional risk model for portfolio construction was made possible by estimating a composite model of forecasted earnings acceleration – a proprietary growth model published in Guerard, Gultekin, and Stone (1997) – and using it as a tilt factor in a portfolio optimization system, such as the BARRA system, described in Rudd and Rosenberg (1979) and Rudd and Clasing (1982), or the APT system, as described in Blin, Bender, and Guerard (1997). The GlobeFlex Virtual Research Team, led in the project by John Guerard, and the GlobeFlex Portfolio Management Team, led in the project by Andrew Mark, worked with Dan Stefek, of Barra, and John Blin, of APT, to quickly develop the variable and portfolios. The resulting CTEF variable was developed using Institutional Brokerage System, Inc. (I/B/E/S) data for the 1990-2001 time period and was in use by early-2002. Let us briefly review the BARRA risk model and its use in realistic portfolio optimization.

Barr Rosenberg and Walt McKibben (1973) estimated the determinants of security betas and standard deviations. Rosenberg and McKibben created 32 variables and a 578-firm sample to estimate the determinants of betas and standard deviations during the 1954-1970 time period. The seventeen-year statistically significant positive determinants of stock standard deviation were the standard deviation of the earnings per share growth rate, leverage, residual risk, and share turnover. The seventeen-year statistically significant negative determinants of stock standard deviation were the accounting beta, the dividend payout ratio, size (the logarithm of total assets), and the S&P Quality variable.

For betas, Rosenberg and McKibben found that the positive and statistically significant determinants were the standard deviation of eps growth, share turnover, the S&P Quality ranking, the price-to-book multiple, leverage, the quick ratio, and the historic beta.[1] Rosenberg and McKibben

[1] Markowitz (1952 and 1959) established the risk-return trade-off analysis for portfolio selection. Sharpe (1964), Lintner (1965), and Mossin (1996) independently developed the Capital Asset Pricing Model in which portfolio returns were a function of the portfolio beta, the sensitivity to market returns. Stock and portfolio returns were functions of the risk-free rate and beta. Black, Jensen, and Sholes (1972) reported that high-beta security had

reported that the negative and statistically significant determinants were the latest annual percentage change in reported earnings, dividend cuts, and gross plant as a percent of total assets, and low price. The Rosenberg and McKibben (1973) estimation formed the basis of the Rosenberg extra-market component study (1974), in which security specific risk could be modeled as a function of financial descriptors or known financial characteristics of the firm. Rosenberg and McKibben reported financial characteristics that were statistically associated with beta during the 1954-1970 period. These statistically significant factors became the basis of the BARRA model, the primary institutional risk model. the significant variables were:

(1) Latest annual proportional change in earnings per share;
(2) Liquidity, as measured by the quick ratio;
(3) Leverage, as measured by the senior debt-to-total assets ratio;
(4) Growth, as measured by the growth in earnings per share;
(5) Book-to-Price ratio;
(6) Historic beta;
(7) Logarithm of stock price;
(8) Standard deviation of earnings per share growth;
(9) Gross plant per dollar of total assets; and
(10) Share turnover.

In 1975, Barr Rosenberg and his associates introduced the BARRA US Equity Model, often denoted USE1.[2] There were 39 industry variables in the BARRA USE1 model. How is the data manipulated and /or normalized to be used in the BARRA USE1 model? First, raw data is normalized by subtracting a mean and dividing through by the variable standard deviation; however, the mean subtracted is the market capitalization weighted mean for each descriptor for all securities in the S&P 500. The relevant variable standard deviation is not the universe standard deviation of each variable, but the standard deviation of the variables for companies with market capitalizations exceeding $50 million. A final transformation occurs when the normalized descriptor is scaled such that its value is one standard

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significantly negative intercepts and low-beta securities had significantly positive intercept, contrary to the traditional form of the CAPM. Multi-factor risk models were developed to address the failing of the CAPM. Barr Rosenberg championed much of this research. Rosenberg et al. (1975), Rosenberg and Marathe (1976, 1979), Rudd and Rosenberg (1979, 1980), and Rudd and Clasing (1982) expanded upon the initial Rosenberg MFM framework. The reader is specifically referred to Rosenberg and Marathe (1976) because the Berkeley Program in Finance working paper specifically reports the underlying equations for the USE1 descriptors.

[2] The BARRA USE1 Model predicted risk, which required the evaluation of the firm's response to economic events, which were measured by the company's fundamentals. There were six descriptors, or risk indexes, in the BARRA model. These descriptors were composite variables primary based on the statistically significant variables in Rosenberg and McKibben (1973). Rudd and Clasing (1982) is an excellent reference for how the BARRA equity model is constructed. BARRA is a proprietary model; that is, the composite model weights are not disclosed. Thus, there were nine factors in the Index of Market Variability, including the historic beta estimate, historic sigma estimate, share turnover for 3 months, trading volume, the log of the common stock price, and a historical alpha estimate, and cumulative range over one year, but without coefficients, one cannot reproduce the model. One can correlate an investment manager's variables with the risk indexes, as we will discuss later in the chapter. The Index of Earnings Variability included the variance of earnings, variance of cash flow, and the covariability of earnings and price. The Index of Low Valuation and Unsuccess included the growth in earnings per share, recent earnings change, relative strength (a price momentum variable), the book-to-price ratio, dividend cuts, and the return of equity. The Index of Immaturity and Smallness included the log of total assets, the log of market capitalization, and net plant / common equity. The Index of Growth Orientation included the dividends-to-earnings ratio (the payout ratio), dividend yield, growth in total assets, the earnings-to-price (ep) multiple, and the typical ep ratio over the past five years. The Graham and Dodd low P/E investment manager would "load up" on The Index of Growth Orientation and would offer investors positive asset selection (good stock picking) only if the portfolio weights differed from weights on the "Growth" Index components. The Index of Financial Risk" included leverage at market and book values, debt-to-assets ratio, and cash flow-to-current liabilities ratio.

deviation above the S&P 500 mean. Every month the monthly stock return in the quarter are regressed as a function of the normalized descriptors. If the firm is typical of the S&P 500 firms, then most of the scaled descriptor values and coefficients should be approximately zero. The monthly residual risk factors are calculated by regressing residual returns (the stock excess return less the predicted beta times the market excess return) versus the six risk indexes and the industry dummy variables.[3] The domestic BARRA E3 (USE3, or sometimes denoted US-E3) model, with some 15 years of research and evolution, uses 13 sources of factor, or systematic, exposures. The sources of extra-market factor exposures are volatility, momentum, size, size non-linearity, trading activity, growth, earnings yield, value, earnings variation, leverage, currency sensitivity, dividend yield, and non-estimation universe. We spent a great deal of time on the BARRA USE1 and USE3 models because 70 of the 100 largest investment managers used the BARRA USE3 Model, according to BARRA on-line advertising in 2002.

The BARRA Model evolved from the USE1 Model discussed in Rudd and Clasing (1982) to the USE3 Model in 1998. We ask two questions: (1) How does USE3 differ from USE1; and why did it matter for asset selection? There are many changes, of importance to many readers. The USE3 used analysts' predictions of the current year and one-year-ahead earnings per share in the earnings yield index which is used in conjunction with the historic and twelve-month trailing earnings-to-price multiples. The analysts' standard deviation of forecasts was a component of the earnings variability component. (Price) Momentum, book-to-market (denoted as "value") and dividend yield, which were separate risk indexes.

Let us address the BARRA Multi Factor Model and its risk indexes using estimated earnings forecasting components of an I/B/E/S-based model of (consensus) forecasted earnings, earnings revisions, and the direction of earnings per share eps revisions of one-year-ahead (FY1) and two-year-ahead (FY2) forecasts. Guerard and Mark (2003) referred to the composite earnings forecasting model as the CTEF model.[4] CTEF is a model of earnings momentum. The CTEF model produced not only higher returns and returns relative to risk than its components, but also higher and more statistically significant asset selection than its components in the Russell 3000 universe during the 1990-2001 period. This discussion was useful because it coverd the issue of variables in the BARRA risk indexes. See Table 1 for Russell 3000 earnings component results in which portfolios of approximately 100 stocks were produced by tilting on the individual and component CTEF variables. The forecast earnings per share for the one-year-ahead and two-year-ahead periods, FEP1 and FEP2, offered negative, but statistically insignificant asset selection. The total active returns were positive, and not statistically significant. The asset selection was negative because the FEP variables produced positive and statistically significant loadings on the risk indexes; particularly the earnings yield index. The factor loading of the FEP variables on the earnings yield risk index was not unexpected given that the earnings yield factor index in the USE3 included the forecast earnings-to-price variable. Thus, there is no multiple factor model benefit to the FEP variables. Note that there were no statistically significant rewards to sector variables in the analysts' forecasts either.

Table 1: Components of the Composite Earnings Forecasting Variable, 1990-2001
Russell 3000 Universe

R3000 Earnings Analysis	Total Active	T-stat	Asset Selection	T-stat	Risk Index	T-stat
FEP1	2.14	1.61	-1.18	-1.17	4.20	4.42

[3] See Rudd and Clasing (1982), p. 115, for the USE1 descriptors.

[4] The CTEF Model was created and estimated combining earnings forecasts, forecasts revisions, and breadth of revisions. Guerard, Takano, and Yamane (1993) reported that earnings forecasts in Japanese stocks pushed out the Markowitz efficient frontier by over 250 basis points, annually, during the 1985 – 1991 period. Guerard, Gultekin and Stone (1997) reported that portfolio excess returns were enhanced by combining earnings forecasts, forecasts revisions, and breadth of revisions into one variable. The reader is referred to Bruce and Epstein (1994) for an excellent collection of articles on earnings forecasting. An outstanding more recent survey of the earnings forecasting literature and its use in hypothesis testing in accounting and finance can be found in Ramnath, Rock, and Shane (2008).

FEP2	1.21	0.91	-1.43	-1.35	3.33	3.35
RV1	0.76	0.69	0.34	0.42	0.92	1.46
RV2	1.40	1.37	1.09	1.31	0.81	1.42
BR1	2.59	2.83	1.85	2.43	1.08	2.15
BR2	2.43	2.36	1.51	1.75	1.09	2.04
CTEF	2.87	2.81	2.07	2.66	1.19	1.70

The monthly revision variables, the RV variables, offered no statistically significant total active returns, or asset selection abilities, as analysts' revisions were incorporated into the USE3 model, as previously mentioned. The breadth variables, BR, produced statistically significant total active returns and asset selection, despite a statistically significant risk index loading. The breadth variable load on the earnings yield and growth risk indexes. Guerard and Mark (2003) examined the BR1 factor risk index loading. The BR1 variable led a portfolio manager to have a positive average active exposure to the earnings yield index, which incorporates the analyst predicted earnings-to-price and historic earnings-to-price measures. The BR1 tilt produced a negative and statistically significant average exposure to size, non-linearity, defined as the cube of normalized market capitalization. This result was consistent with analyst revisions being more effective in smaller capitalized securities. The BR1 variable tilt led the portfolio manager to have a positive and statistically significant exposure to the growth factor index, composed of the growth in the dividend payout ratio, the growth rates in total assets and earnings per share during the past five years, recent one-year earnings growth, and the variability in capital structure. The CTEF variable produced statistically significant total active returns and asset selection. The CTEF variable loading on the risk index was statistically significant at the 10 percent level because of its loading on the earnings yield and non-linear size indexes, as was the case with its breadth components. See Table 2.

Table 2: CTEF Variable Factor Exposures, Russell 1000 Universe

Attribution Analysis

Annualized Contributions to Risk Index Return

Source of Return	Average Active Exposure	Contribution (% Return) Average [1]	Variation [2]	Total [1+2]	Total Risk (% Std Dev)	Info Ratio	T-Stat
VOLATILITY	-0.01	0.01	-0.07	-0.06	0.17	-0.32	-1.12
MOMENTUM	0.12	-0.07	0.08	0.01	0.60	0.03	0.11
SIZE	-0.20	0.36	-0.09	0.27	0.93	0.24	0.83
SIZE NON-LINEARITY	-0.02	0.02	0.03	0.05	0.10	0.44	1.52
TRADING ACTIVITY	0.00	0.00	0.01	0.01	0.11	0.11	0.37
GROWTH	-0.05	0.05	0.03	0.08	0.14	0.48	1.65
EARNINGS YIELD	0.13	0.66	-0.12	0.55	0.40	1.20	4.13
VALUE	0.06	0.03	0.02	0.06	0.17	0.30	1.03
EARNINGS VARIATION	0.02	-0.02	0.00	-0.03	0.10	-0.21	-0.73
LEVERAGE	0.06	-0.01	-0.04	-0.04	0.17	-0.23	-0.80
CURRENCY SENSITIVITY	-0.02	0.01	-0.05	-0.04	0.11	-0.32	-1.11
YIELD	0.04	0.01	-0.04	-0.04	0.14	-0.24	-0.81

NON-EST UNIVERSE	0.00	0.00	0.01	0.01	0.04	0.20	0.68
Total				0.82	1.16	0.62	2.13

The CTEF model offered statistically significant asset selection in a multiple factor model framework.

The Frank Russell large market capitalization universe (the Russell 1000), middle market capitalization (Russell Mid Cap), small capitalization (Russell 2000) and small- and middle market capitalization (Russell 2500) universes were used in the Guerard and Mark (2003) CTEF tests. Higher excess returns, greater asset selection and stock market inefficiency were found in the smaller stocks of the R3000 universe.

Guerard and Mark estimated a nine-factor regression model to identify the determinants of stock returns using the Bloch, Guerard, Markowitz, Todd, and Xu (1993) the weighted latent root regression model, WLRR, which used the Beaton-Tukey (1974) bisquare procedure in its robust regression and latent root regression to address the problem of multicollinearity. The CTEF and WLRR models produced highly statistically significant active returns and asset selection.

In this analysis we will show how forecasted earnings acceleration produces highly statistically significant stock selection in global and U.S. stock universes for the 1997 – 2016 time period. Portfolios optimized using the CTEF, REG8, REG9CTEF, and REG10 models produce higher active and specific returns in non-U.S. stocks, whereas only CTEF works in the U.S.

30.3 A LITERAURE REVIEW OF EXPECTED RETURNS MODELING AND AN EVOLUTION OF STOCK SELECTION MODELS

There are many different approaches to security valuation and the creation of expected returns. One seeks to select expected returns inputs that are associated statistically with stock returns. Subramanian, Suzuki, Makedon, and Carey (2016) classify variables expected returns variables as valuation, momentum and growth. The expected returns input normally consists of variables that are denoted anomalies, which can be used as inputs to the portfolio construction process in order to produce portfolios that outperform the market. The early approaches to security analysis and stock selection involved the use of valuation techniques that used reported earnings and other financial data such as book value, cash flow, sales, net working capital. Graham and Dodd (1934) recommended that stocks be purchased on the basis of the price-to-earnings (P/E) ratio. They suggested that no stock should be purchased if its price-to-earnings ratio exceeded 1.5 times the P/E multiple of the market. Graham and Dodd established the P/E criteria, and it was then discussed by Williams (1938), who wrote the monograph that influenced Harry Markowitz's thinking on portfolio construction. It is interesting that Graham and Dodd proposed the low P/E model at the height of the Great Depression. Basu (1977) reported evidence supporting the low P/E model. Researchers have gone beyond using just one or two of the standard value ratios (EP and BP), and have included the cash-to-price ratio (CP) and/or the sales-to-price ratio (SP), among others.[5] There is an extensive body of literature on the impact of individual value ratios and variables on the cross-section of stock returns in the pre-2002 time period.

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[5] The major papers on the combination of value ratios for the prediction of stock returns (including at least CP and/or SP) include those of Jacobs and Levy (1988), Chan, Hamao, and Lakonishok (1991), Fama and French (1992 and 1995), Bloch, Guerard, Markowitz, Todd, and Xu (1993), Lakonishok, Shleifer, and Vishny (1994), Haugen and Baker (1996). Fundamental variables enhanced portfolio returns over the long-run.

Chan et al. (1991) used seemingly unrelated regressions (SUR) to model CAPM excess returns as functions of traditional fundamental variables such as earnings, book values and cash flows relative to price, denoted as EP, BP and CP. Moreover, size was measured as the natural logarithm of market capitalization (LS).[5] Betas were estimated simultaneously, and cross-sectional correlations of residuals were addressed. When fractal portfolios

In 1991, Harry Markowitz developed an equity research group at Daiwa Securities Trust Company, in Jersey City, NJ. Bloch et al. (1993) built fundamental-based stock selection models for Japanese and U.S. stocks. The investable stock universe was the first section, non-financial Tokyo Stock Exchange common stocks from January 1975 to December 1990 in Japan, and the 1,000 largest market-capitalized common stocks from November 1975 to December 1990 in the U.S. They found that a series of Markowitz (1952, 1959, and 1976) mean-variance efficient portfolios using the higher EP values in Japan underperformed the universe benchmark, whereas BP, CP, and SP (sales-to-price, or sales yield) variables outperformed the universe benchmark. For the U.S., the optimized portfolios using the BP, CP, SP, and EP variables outperformed the U.S. S&P 500, providing support for the Graham and Dodd concept of using the relative rankings of value-focused fundamental ratios to select stocks.[6] Bloch et al. (1993) used relative ratios as well as current ratio values. Not only might an investor want to purchase a low P/E stock, one might also wish to purchase when the ratio is at a relatively low value compared to its historical value, in this case a low P/E relative to its average over the last five years. Eight factors were used in the quarterly, cross-sectional regressions in Japan and the U.S. Bloch, Guerard, Markowitz, Todd, and Xu (1993) estimated Equation (1) to assess empirically the relative explanatory power of each of the eight variables in the equation to estimate the determinants of total stock returns, TR. We refer to this model as REG8.

$$\text{TR} = w_0 + w_1\text{EP} + w_2\text{BP} + w_3\text{CP} + w_4\text{SP} + w_5\text{REP} + w_6\text{RBP} + w_7\text{RCP} + w_8\text{RSP} + e_t \qquad (1)$$

where: EP = [earnings per share]/[price per share] = earnings-price ratio;

BP = [book value per share]/[price per share] = book-price ratio;

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were constructed by sorting on the EP ratio, the highest EP quintile portfolio outperformed the lowest EP quintile portfolio, and the EP effect was not statistically significant. The portfolios composed of and sorted by the highest BP and CP outperformed the portfolios composed of the lowest BP and CP stocks. In the authors' multiple regressions, the size and book-to-market variables were positive and statistically significant. The EP coefficient was negative and statistically significant at the 10% level. Applying an adaptation of the Fama and MacBeth (1973) time series of portfolio cross-sections to the Japanese market produced negative and statistically significant coefficients on EP and size, but positive and statistically significant coefficients for the BP and CP variables. Chan et al. (1991, p. 1760) summarized their findings as follows: "The performance of the book-to-market ratio is especially noteworthy; this variable is the most important of the four variables investigated."

In a thorough assessment of value versus growth in the U.S., Lakonishok et al. (1994) examined the intersection of the Compustat and CRSP databases for annual portfolios for NYSE and AMEX common stocks, April 1963 to April 1990. Their value measures were three current value ratios: EP, BP and CP. Their growth measure was the five-year average annual growth of sales (GS). They performed three types of tests: a univariate ranking into annual decile portfolios for each of the four variables, bivariate rankings on CP (value) and GS (growth, glamour), and finally a multivariate regression adaptation of the Fama and MacBeth (1973) time series pooling of cross-sectional regressions. The univariate regression coefficient for GS was significantly negative. The EP, BP, and CP coefficients were all significantly positive. When Lakonishok et al. performed a multivariate regression using all four variables, they found significantly positive coefficients for BP and EP (but not CP), and significantly negative coefficients for GS. Lakonishok et al. (1994) concluded that buying out-of-favor value stocks outperformed growth (glamour) stocks during the period April 1968 to April 1990, that future growth was difficult to predict from past growth alone, that the actual future growth of the glamour stocks was much lower than past growth, relative to the growth of value stocks, and that the value strategies were not significantly riskier than growth (or 'glamour') strategies ex post.

[6] One finds the Price/Earnings, Price/Book and Price/Sales ratios listed among the accounting anomalies by Levy (1999, p. 434). Levy also discusses the dividend yield as a (positive) stock anomaly. Malkiel (1996) cites evidence in support of buying low P/E, low P/B, and high D/P (dividend yield) stocks for a good performance, provided that the low P/E stocks have modest growth prospects (pp. 204-210). Malkiel speaks of a "double bonus"; that is, if growth occurs, earnings increase, and the price-to-earnings multiple may increase, driving the price up even further. Of course, should growth fail to occur, both earnings and the P/E multiple may fall.

CP = [cash flow per share]/[price per share] = cash flow-price ratio;

SP = [net sales per share]/[price per share] = sales-price ratio;

REP = [current EP ratio]/[average EP ratio over the past five years];

RBP = [current BP ratio]/[average BP ratio over the past five years];

RCP = [current CP ratio]/[average CP ratio over the past five years];

RSP = [current SP ratio]/[average SP ratio over the past five years];

Given concerns about both outlier distortion and multicollinearity, Bloch et al. (1993) tested the relative explanatory and predictive merits of alternative regression estimation procedures: OLS; robust regression using the Beaton and Tukey (1974) bi-square criterion to mitigate the impact of outliers; latent roots to address the issue of multicollinearity (see Gunst, Webster, & Mason, 1976); and weighted latent roots, denoted WLRR, a combination of robust and latent roots. Bloch et al. (1993) used the estimated regression coefficients to construct a rolling horizon return forecast. The predicted returns and predictions of risk parameters were used as inputs for a mean-variance optimizer (see Markowitz, 1987) to create mean-variance efficient portfolios in financial markets in both Japan and the U.S. Bloch et al. (1993) reported several results. First, they compared OLS and WLRR techniques, inputting the expected return forecasts produced by each method into a mean-variance optimizer. The WLRR-constructed composite model portfolio produced higher Sharpe ratios and geometric means than the OLS-constructed composite model portfolio in both Japan and the U.S., indicating that controlling for both outliers and multi-collinearity is important when using regression-estimated composite forecasts. Second, Bloch et al. (1993) quantified the survivor bias and found that it was not statistically significant in either Japan or the U.S. for the period tested. Third, they investigated period-to-period portfolio revision and found that tighter turnover and rebalancing triggers led to higher portfolio returns for value-based strategies. Finally, Markowitz and Xu (1994) developed a test for data mining.[7] In addition to testing the hypothesis of data mining, the test can also be used to estimate and assess the expected differences between the best test model and the average of simulated policies. We will refer to the eight-factor model as REG8, or the Markowitz model, in this analysis.

Studies of the effectiveness of corporate earnings forecasting variables and models can be found in Bruce and Epstein (1994).[8] Analysts' forecasts of earnings per share (eps), eps revision, and the

[7] Bloch et al. (1993) wrote their manuscript in 1991. At the time of the original estimation of eight-factor regression model, the international Institutional Estimation Brokerage Service (I/B/E/S) was only four years old, having started in 1987, and did not have sufficient data for model building and testing such that the models with earnings forecasts could pass the Markowitz and Xu (1994) Data Mining Corrections test.

[8] The Bruce and Epstein and Brown works contain much of the rich history of earnings forecasting and resulting excess returns. Researchers such as Elton, Gruber, and Gultekin, who developed I/B/E/S database and published the initial research (1981 and 1984) and Hawkins, Chamberlain, and Daniel (1984). The Elton et al. (1981) paper is one most influential analyses in earnings forecasting and security analysis.

Hawkins, Chamberlain, and Daniel (1984) which reported large excess returns for domestic stocks, which have the largest positive monthly earnings revisions for the period 1975–1980. Wheeler (1994) developed and tested a U.S.-only stock strategy in which analyst forecast revision breadth, defined as the number of upward forecast revisions less the number of downward forecast revisions, divided by the total number of estimates, was the criterion for stock selection. Wheeler found statistically significant excess returns from the breadth strategy. Thus, earnings forecasts per share, earnings forecast revisions, and earnings forecast breadth had all been documented by 1994. Guerard, Gultekin, and Stone (1997) created a composite forecasting variable consisting of consensus analysts' forecasts, forecast revisions and the breadth variables, which they referred to as a proprietary direction of eps forecast revisions were incorporated into the Institutional Broker Estimation Services (I/B/E/S) in-print database in July 1972. The I/B/E/S database has computer-readable data from January 1976, domestically, and January 1987, internationally, see Brown (2000). We present evidence in this section that the I/B/E/S database has been a source of highly statistically significant excess returns. We refer the reader to Brown (2000) which contains about 570 abstracts of I/B/E/S studies. Analysts' forecast variables enhanced portfolio returns over the long-run. Guerard and Mark (2003) tested Equation (2) as a stock selection model which we refer to as REG9CTEF.

$$TR_{t+1} = a_0 + a_1 EP_t + a_2 BP_t + a_3 CP_t + a_4 SP_t + a_5 REP_t + a_6 RBP_t + a_7 RCP_t + a_8 RSP_t + a_9 CTEF_t + e_t , \tag{2}$$

where:

	EP	=	[earnings per share]/[price per share] = earnings-price ratio;
	BP	=	[book value per share]/[price per share] = book-price ratio;
	CP	=	[cash flow per share]/[price per share] = cash flow-price ratio;
	SP	=	[net sales per share]/[price per share] = sales-price ratio;
	REP	=	[current EP ratio]/[average EP ratio over the past five years];
	RBP	=	[current BP ratio]/[average BP ratio over the past five years];
	RCP	=	[current CP ratio]/[average CP ratio over the past five years];
	RSP	=	[current SP ratio]/[average SP ratio over the past five years];
	CTEF	=	consensus earnings-per-share I/B/E/S forecast, revisions and breadth; and
	e	=	randomly distributed error term.

There is an equally extensive body of literature of the impact of price momentum variables on the cross-section of stock returns. Price momentum, or the non-random character of stock market prices, have been studied since Bachelier in 1900, but the availability of much of the early, pre-1964 research was made far more accessible in Cootner (1964).[9] Influential recent researchers such as Conrad, Kaul, and Nimalendran (1991), Conrad and Kaul (1993), Conrad and Kaul (1998), and Lo, Mamaysky, and Wang

growth variable, PRGR, and reported that the composite earnings variable, when added to eight-factor model as a ninth variable, averaged a relative weight of 33%. This result complements that of Lakonishok et al. (1994) in showing that rank-ordered portfolio returns have significant value and growth components. Guerard (1997) reported the dominance of the (same) consensus earnings efficiency variable, referred to as CTEF, relative to analysts' revisions, forecasted earnings yields, and breadth in generating excess returns.

Womack (1996) Guerard, Gultekin and Stone (1997), Hong, Kubik, and Solomon (2000), Hong and Kubik (2003), and Guerard, Markowitz, and Xu (2015) are among the thousands of studies of analysts' forecasting efficiency and how analysts' forecasts enhance portfolio returns.

[9] The classic Cootner edited volume reprinted the works of Bachelier (translated), Kendall, Osborne, Working, Cowles, Granger, Fama, Mandelbrot, and Samuelson, among others. It is interesting to note that these researchers published in economic, business, statistical, operations research, and industrial management journals. The Cootner volume papers reported evidence of efficient and inefficient markets.

(2000) have extended the technical analysis and price momentum literature. Most importantly for our analysis, Conrad and Kaul (1998) reported the mean-reversion of stock returns in the very short run, one week or one month, and the medium-term persistence of momentum to drive stock prices higher in the 3, 6, 9, 12, and 18-month time horizons over the 1926 -1988 and 1926-1989 time periods.[10] Jagadeesh and Titman construct portfolios based on six-months of positive price momentum, hold the portfolios for six months, and earn excess returns of 12.01% over the 1965-1989 time period. Medium-term momentum is an important, and persistent, risk premium. In the very long-run, 24 and 36-months in Conrad and Kaul (1998), momentum returns become very negative. Lo, Mamaysky, and Wang (2000) produced a definitive study of technical analysis over the 1962 -1996 time period and found that technical patterns produced incremental returns, particularly for NASDAQ stocks. Price momentum and technical analysis variables enhanced portfolio returns over the long-run.

Guerard, Xu, and Gultekin (2012) added the Guerard et al. (1997) composite earnings forecasting variable CTEF and the Fama and French (1998) PM122 variable, defined as P(t-2)/P(t-12), to stock selection model, to create a ten-factor stock selection model for the U.S. expected returns, which they referred to as the USER model.[11] See equation (3).

$$\begin{aligned} \mathrm{TR}_{t+1} = a_0 + a_1\mathrm{EP}_t + a_2\,\mathrm{BP}_t + a_3\mathrm{CP}_t + a_4\mathrm{SP}_t + a_5\mathrm{REP}_t + a_6\mathrm{RBP}_t + a_7\mathrm{RCP}_t \\ + a_8\mathrm{RSP}_t + a_9\mathrm{CTEF}_t + a_{10}\mathrm{PM}_t + e_t\,, \end{aligned} \tag{3}$$

where: EP = [earnings per share]/[price per share] = earnings-price ratio;

BP = [book value per share]/[price per share] = book-price ratio;

CP = [cash flow per share]/[price per share] = cash flow-price ratio;

SP = [net sales per share]/[price per share] = sales-price ratio;

REP = [current EP ratio]/[average EP ratio over the past five years];

RBP = [current BP ratio]/[average BP ratio over the past five years];

RCP = [current CP ratio]/[average CP ratio over the past five years];

RSP = [current SP ratio]/[average SP ratio over the past five years];

CTEF = consensus earnings-per-share I/B/E/S forecast, revisions and breadth;

PM = price momentum; and

e = randomly distributed error term.

Guerard, Markowitz, and Xu (2013) and Guerard, Rachev, and Shao (2013) estimated the ten-factor model for all global stocks included in the FactSet database over the period January 1997–December 2011. They referred to the global expected returns model as the GLER model. The GLER model produced highly statistically significant active returns and better stock selections than the USER

[10] A second-order effect of CTEF is that the forecasted earnings acceleration has a positive exposure to the Conrad-Gaul medium-term momentum, 3-12 months, and CTEF produces a medium-term momentum factor contribution that is statistically significant.

[11] Bush and Boles (1983) and Brush (2001) tested a PM121 price momentum variable, defined as P(t-1)/P(t-12).

model over the corresponding period. [12]

The recent literature on financial anomalies is summarized by Levy (1999), Fama and French (2008), Levy (2012), Guerard, Markowitz, and Xu (2013, 2014, and 2015), and Jacobs and Levy (2017).

30.4 APT AND AXIOMA RISK MODELS: CONSTRUCTING MEAN-VARIANCE EFFICIENT FRONTIERS

John Blin, Steve Bender, and John Guerard (1997) and Guerard (2012) demonstrated the effectiveness of the APT, Sungard APT, and FIS APT systems in portfolio construction and management. Let us review the APT approach to portfolio construction. The estimation of security weights, *w*, in a portfolio is the primary calculation of Markowitz's portfolio management approach. The issue of security weights will be now considered from a different perspective. The security weight is the proportion of the portfolio's market value invested in the individual security:

$$w_s = \frac{MV_s}{MV_p} \qquad (4)$$

where w_s = portfolio weight insecurity s,
MV_s = value of security s within the portfolio,
and MV_p = the total market value of portfolio.

The active weight of the security is calculated by subtracting the security weight in the (index) benchmark, b, from the security weight in the portfolio, p.

Blin and Bender created a multi-factor risk model within their APT risk model based on forecast volatility.

$$\sigma_p = \sqrt{52\left(\sum_{c=1}^{c}\left(\sum_{i=1}^{s} w_i \beta_{i,c}\right)^2 + \sum_{i=1}^{s} w_i^2 \varepsilon_{i,w}^2\right)} \qquad (5)$$

Where σ_p = Forecast Volatility of Annual Portfolio Return,
C = Number of Statistical Components in the Risk Model,

w_i = Portfolio weight in security i,
$\beta_{i,c}$ = The loading (beta) of security i on risk component c,
$\varepsilon_{i,w}$ = Weekly Specific Volatility of Security i.

The Blin and Bender systematic volatility is a forecast of the annual portfolio standard deviation expressed as a function of each security's systematic APT components. The systematic risk is the portfolio beta-squared times the market variance.

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[12] That is, global stock selection models outperformed domestic stock selection models. Thus, U.S. investors should prefer global portfolios in order to maximize portfolio returns.

$$\sigma_{\beta p} = \sqrt{52\sum_{c=1}^{c}\left(\sum_{i=1}^{s} w_i \beta_{i,c}\right)^2} \tag{6}$$

Portfolio specific volatility is a forecast of the annualized standard deviation associated with each security's specific return.

$$\sigma_{\varepsilon p} = \sqrt{52\sum_{i=1}^{s} w_i^2 \varepsilon_{i,w}^2} \tag{7}$$

The tracking error, te, is a measure of volatility applied to the active return of funds (or portfolio strategies) that are indexed versus (against) a benchmark, which is often an index. Portfolio tracking error is defined as the standard deviation of the portfolio return less the benchmark return over one year.

$$\sigma_{te} = \sqrt{E(((r_p - r_b) - E(r_p - r_b))^2)} \tag{8}$$

σ_{te} = annualized tracking error,
r_p = actual portfolio annual return,
r_b = actual benchmark annual return.

The APT-reported tracking error is the forecast tracking error for the current portfolio versus the current benchmark for the coming year.

$$\sigma_{te} = \sqrt{52\left(\sum_{c=1}^{c}\left(\sum_{i=1}^{s} w_{i,p} - w_{i,b}\right)\beta_{i,c}\right)^2 + \sum_{i=1}^{s}\left(w_{i,p} - w_{i,b}\right)^2 \varepsilon_{i,w}^2} \tag{9}$$

Systematic tracking error of a portfolio is a forecast of the portfolio's active (annual) return as a function of the securities' returns associated with APT risk model components.

$$\sigma\beta_{te} = \sqrt{52\sum_{c=1}^{c}\left(\sum_{i=1}^{s}\left(w_{i,p} - w_{i,b}\right)\beta_{i,c}^2\right)} \tag{10}$$

Portfolio specific tracking error can be written as a forecast of the annual portfolio active return associated with each security's specific behavior.

$$\sigma_{\varepsilon te} = \sqrt{52\sum_{i=1}^{s}\left(w_{i,p} - w_{i,b}\right)^2 \varepsilon_{i,w}^2} \tag{11}$$

The marginal volatility of a security, the measure of the sensitivity of the portfolio volatility, is relative to the change in the specific security weight. We must know the relative contribution of each security to the risk of the portfolio. The APT marginal security volatility may be written as:

$$\partial_s = \frac{\sqrt{52\left(\sum_{c=1}^{e}\beta_{s,c}\left(\sum_{i=1}^{s} w_i \beta_{i,c}\right) + w_s \varepsilon_{s,w}^2\right)}}{\sqrt{52\left(\sum_{c=1}^{c}\left(\sum_{i=1}^{s} w_i \beta_{i,c}\right)^2 + \sum_{i=1}^{s} w_i^2 \varepsilon_{i,w}^2\right)}} \tag{13}$$

The marginal security systematic volatility is the partial derivative of the systematic volatility of the portfolio relative to the security weight. In the King's English, the marginal tracking error measures the sensitivity of the tracking error relative to the marginal change in the security active weight. If a position taken in a security leads to an increase in the portfolio's volatility, then the security is said to create a positive contribution to risk. A negative contribution to risk occurs when a security reduces the portfolio volatility such as a long position on a security with a negative beta or a short position on a security with a positive beta. Obviously, the contribution to risk depends upon the security weight and the security's beta to the overall portfolio. The security contribution to tracking error, ξ_s, reflects the security's contribution to the tracking error of a portfolio considering the security return that is undiversified at the active portfolio level.

The portfolio Value-at-Risk (VaR) is the expected maximum loss that a portfolio could produce over one year. The APT measure of portfolio risk estimating the magnitude that the portfolio return may deviate from the benchmark return over one year is referred to as TaR, or "Tracking-at-Risk"™.

$$T_p^V = \sqrt{\left(\frac{1}{\sqrt{1-x}}\sigma_s\right)^2 + \left(\sqrt{2}erf^{-1}(x)\sigma_\varepsilon\right)^2} \tag{14}$$

where T_p^V = TaR™
x = Desired confidence level of TaR™
σ_s = Portfolio systematic tracking error,
$Erf^{-1}(x)$ = inverse error function,
and σ_ε = Portfolio specific tracking error.

TaR is composed of systematic and specific components. What is the economic importance of tracking error at risk? First, TaR helps the assert manager assess downside risk. Second, by optimizing portfolios where systematic risk is more important than specific risk, one produces high Information Ratios, IRs, than equally-weighting systematic and specific risk or using only total risk (Markowitz, 1959). TaR specifically addresses fat tails in stock return distributions. Third, as portfolios becomes diversified, the R-squared statistics of portfolio returns rise, and the optimal TaR ratio to relative tracking errors rise, to 1.645 (unsystematic risk is weighted 0.345)[13].

Blin and Bender during the 1987-1997 period, developed an APT software system which estimated a 20 factor beta model of covariances based on 3.5 years of weekly stock returns data. The Blin and Bender Arbitrage Pricing Theory (APT) model followed the Ross factor modeling theory, but Blin and Bender estimated betas from 20-24 orthogonal factors. Estimating more factors than necessary at each point in time is not harmful, as long as the 20 orthogonal factors are orthogonal. Dhrymes, Friend and Gultekin (1984) and Dhrymes, Friend. Gultekin, and Gultekin (1985) estimated four factors. Blin and Bender never sought to identify their factors with economic variables.

We refer to APT Mean-Variance Tracking Error at Risk optimization as MVTaR. The APT optimizer maximizes the Sharpe ratio, the portfolio excess return relative to the portfolio standard

[13] Personal conversation with John Blin and the authors in the APT New York office, February 2002.APT showed that holding the tracking error constant, TaR rose as systematic risk rose in total variance. John Blin taught us that fat tails are far too frequent than one might expect in a normal distribution (in 2002). The normal distribution limits returns beyond three standard deviations to 1% of the cases (one-tail) whereas the Bienayme-Chebyshev theorem allows up to 11% of cases to lie beyond three standard deviations. Wright (2007) popularized the APT and Nassim Taleb fat tails analysis.

deviation, see Sharpe (1966, 1992). [14] The author reported highly statistically significant portfolio results in U.S. and Non-US markets with that APT TaR portfolios.[15] Guerard, Rachev and Shao (2013) and Guerard, Markowitz, and Xu (2015) reported the highly statistically significant excess returns (and specific returns) effectiveness of an APT MVTaR optimization analysis of CTEF in global markets during the 1997 - 2011 time period and Guerard, Markowitz, and Xu (2014) reported CTEF effectiveness in U.S. markets over the corresponding time period.

Another commercially-available risk model is the Axioma Risk Model. The Axioma Robust Risk Model[16] is a multi-factor risk model, in the tradition of the Barra model. Axioma offers both U.S. and world fundamental and statistical risk models. The Axioma Risk Models use several statistical techniques to efficiently estimate factors. The ordinary least squares residuals (OLS) of beta estimations are not homoskedastic; that is, when one minimizes the sum of the squared residuals to estimate factors using OLS, one finds that large assets exhibit lower volatility than smaller assets. A constant variance of returns is not found. Axioma uses a weighted least squares (WLS) regression, which scales the asset residual by the square root of the asset market capitalization (to serve as a proxy for the inverse of the residual variance). Robust regression, using the Huber M Estimator, addresses the issue and problem of outliers. (Asymptotic) Principal components analysis (PCA) is used to estimate the statistical risk factors. A subset of assets is used to estimate the factors and the exposures and factor returns are applied to other assets.

Axioma has pioneered two techniques to address the so-called under-estimation of realized tracking errors, particularly during the 2008 Financial Crisis. The first technique, known as the Alpha Alignment Factor, AAF, recognizes the possibility of missing systematic risk factors and makes amends to the greatest extent that is possible without a complete recalibration of the risk model that accounts for the latent systematic risk in alpha factors explicitly. In the process of doing so, AAF approach not only improves the accuracy of risk prediction, but also makes up for the lack of efficiency in the optimal portfolios. The second technique, known as the Custom Risk Model, CRM, proposes the creation of a

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[14] There are several criteria to be used in portfolio construction. First, the Geometric Mean of the portfolio is maximized over time (Markowitz, 1959, 1976, and 2002), Latane (1959), and Levy (2017). The Sharpe Ratio, ShR [Sharpe, 1966, 1970, 1992] should be maximized. Grinold and Kahn (1999) use the Information Ratio (IR*)* as a portfolio construction objective to be maximized, which measures the ratio of residual return to residual risk.

[15] Guerard (2012) constructed an Equal Active Weighting (EAW) Efficient Frontier varying the risk aversion levels. The EAW process allows security weights in the portfolio to deviate no more than two percent from the benchmark weights, a process based on Markowitz's Enhanced Index Tracking (EIT) procedure. The portfolio construction process uses eight percent monthly turnover, after the initial portfolio is created, and 150 basis points of transactions costs each way, globally, 125 basis points, domestically. The MQ optimized portfolios outperform the U.S. market, (defined here as the Russell 3000 Growth Index, R3G), and the Global Market, (defined here as the Morgan Stanley Capital International (MSCI) All Country World Growth (ACWG) Index). The index returns are often referred to as the Benchmark, denoted B. The analyst-covered stocks in the U.S. are ranked on monthly MQ based criteria from January 1998 – December 2009. The sources of the MQ enhanced excess returns are exposures to size (buying smaller-capitalized securities), earnings yield, financial leverage, value, momentum risk indexes, and asset selection. Asset selection is statistically significant at the 10 percent level in the Russell 3000 Growth universe for the 1998-2009 time period for a lambda of 500 estimation. Asset selection of the MQ model is statistically significant at the five percent level in the ACWG universe in the 1998-2009 time period and exceeds the asset selection of the MQ model in the R3G universe. Global markets have historically been more inefficient than the U.S. markets [Bloch et. al. (1993)]. In summary, the MQ selection model produces asset selection of 269 basis points (statistically significantly at the 10 percent level) in the U.S. and 590 basis points in the Global market (statistically significantly at the 5 percent level) during the November 2000 - December 2009 time period, Emerging Markets, EM, became an investable universe for many investors and EM expanded the risk-return trade-off of McKinley Capital Management (MCM) investors.

[16] Axioma Robust Risk Model Handbook, January 2010.

custom risk model by combing the factors used in both the expected-return and risk models, which does not address the factor alignment problem that is due to constraints.[17]

The naïve application of the portfolio optimization has the unintended effect of magnifying the sources of misalignment. The optimized portfolio underestimates the unknown systematic risk of the portion of the expected returns that is not aligned with the risk model. Consequently, it overloads the portion of the expected return that is uncorrelated with the risk factors. The empirical results in a test-bed of real-life active portfolios based on client data show clearly that the above-mentioned unknown systematic risk is a significant portion of the overall systematic risk and should be addressed accordingly. Saxena and Stubs (2012) reported that the earning-to-price (E/P) and book-to-price (B/P) ratios used in USER Model and Axioma Risk Model have average misalignment coefficients of 72% and 68%, respectively. While expected-return and risk models are indispensable components of any active strategy, there is also a third component, namely the set of constraints that is used to build a portfolio. Saxena and Stubbs (2012) proposed that the risk variance-covariance matrix *C* be augmented with additional auxiliary factors in order to complete the risk model. The augmented risk model has the form of

$$C_{new} = C + \sigma_{\underline{\alpha}}^2 \underline{\alpha} \cdot \underline{\alpha'} + \sigma_{\underline{\gamma}}^2 \underline{\gamma} \cdot \underline{\gamma'} \,, \tag{15}$$

where $\underline{\alpha}$ is the alpha alignment factor (AAF), σ_α is the estimated systematic risk of $\underline{\alpha}$, $\underline{\gamma}$ is the auxiliary factor for constrains, and σ_γ is the estimated systematic risk of $\underline{\gamma}$. The alpha alignment factor $\underline{\alpha}$ is the unitized portion of the uncorrelated expected-return model, i.e., the orthogonal component, with risk model factors. Saxena and Stubbs (2012) reported that the AAF process pushed out the traditional risk model-estimated efficient frontier. Saxena and Stubbs (2015) refer to as alpha in the augmented regression model as the implied alpha. According to Saxena and Stubbs (2015), the base risk model, BRM, assumes that any factor portfolio uncorrelated with X-common risk factors has only idiosyncratic risk. Z is the exposure matrix associated with systematic risk factors missing from the base risk model, and the risk model fails to account for the systematic risk of portfolios with exposure to the Z factors. Saxena and Stubbs (2015) report that there is a small increment to specific risk compared to its true systematic risk.

Saxena and Stubbs (2012) applied their AAF methodology to the USER model, running a monthly backtest based on the above strategy over the time period 2001–2009 for various tracking error values of σ chosen from {4%, 5%… 8%}. For each value of σ, the backtests were run on two setups,which were identical in all respects except one, namely that only the second setup used the AAF methodology ($\sigma_\alpha = 20\%$). Axioma's fundamental medium-horizon risk model (US2AxiomaMH) is used to model the active risk constraints. Saxena and Stubbs (2012) analyzed the time series of misalignment coefficients of alpha, implied alpha and the optimal portfolio, and found that almost 40—60% of the

[17] Several practitioners have decided to perform a "post-mortem" analysis of mean-variance portfolios, attempted to understand the reasons for the deviation of ex-post performances from ex-ante targets, and used their analysis to suggest enhancements to mean-variance optimization inputs, in order to overcome the discrepancy. Lee and Stefek (2008) and Saxena and Stubbs (2012) define this as a factor alignment problem (FAP), which arises as a result of the complex interactions between the factors used for forecasting expected returns, risks and constraints.[17] While predicting expected returns is exclusively a forward-looking activity, risk prediction focuses on explaining the cross-sectional variability of returns, mostly by using historical data. Expected-return modelers are interested in the first moment of the equity return process, while risk modelers focus on the second moments. These differences in ultimate goals inevitably introduce different factors for expected returns and risks. Even for the "same" factors, expected-return and risk modelers may choose different definitions for good reasons. Constraints play an important role in determining the composition of the optimal portfolio. Most real-life quantitative strategies have other constraints that model desirable characteristic of the optimal portfolio. For example, a client may be reluctant to invest in stocks that benefit from alcohol, tobacco or gambling activities on ethical grounds, or may constrain their portfolio turnover so as to reduce their tax burden.

alpha is not aligned with the risk factors. The alignment characteristics of the implied alpha are much better than those of the alpha. Among other things, this implies that the constraints of the above strategy, especially the long-only constraints, play a proactive role in containing the misalignment issue. In addition, not only do the orthogonal components of both the alpha and the implied alpha have systematic risk, but the magnitude of the systematic risk is comparable to that of the systematic risk associated with a median risk factor in US2AxiomMH. Saxena and Stubbs (2012) showed the predicted and realized active risks for various risk target levels and noted the significant downward bias in risk prediction when the AAF methodology is not employed.[18] The realized risk-return frontier demonstrates that not only does using the AAF methodology improve the accuracy of the risk prediction, it also moves the ex-post frontier upwards, thereby giving ex-post performance improvements. In other words, the AAF approach recognizes the possibility of missing systematic risk factors and makes amends to the greatest extent that is possible without a complete recalibration of the risk model that accounts for the latent systematic risk in alpha factors explicitly. In the process of doing so, AAF approach not only improves the accuracy of risk prediction, but also makes up for the lack of efficiency in the optimal portfolios.[19] Saxena and Stubbs (2015) extended their 2012 Journal of Investing research and reported positive frontier spreads.

Guerard, Markowitz, and Xu (2015) tested CTEF and a ten-factor regression-based model of global expected returns, GLER, during the 1997- 2011 time period. The authors reported that the geometric means and Sharpe ratios increase with the targeted tracking errors; however, the information ratios are higher in the lower tracking error range of 3–6%, with at least 200 stocks, on average, in the optimal portfolios. They reported that statistically-based risk models using principal components, such as Sungard APT and Axioma, produce more efficient trade-off curves than fundamentally-based risk model using our variables. Risk was underestimated substantially at higher targeted tracking errors, with the AAF producing higher Sharpe ratios and information ratios in both Fundamental and Statistical risk model tests, particularly in the 7–10% targeted tracking error range. The Axioma Statistical Risk Model was sufficient for CTEF whereas the Axioma Statistical Model with AAF of 20% was optimal for the GLER Model.

The Markowitz (1952 and 1959) portfolio construction approach seeks to identify the efficient frontier, the point at which returns are maximized for a given level of risk, or risk is minimized for a given level of return. The portfolio expected return, E(Rp), is calculated by taking the sum of the security weights multiplied by their respective expected returns. The portfolio standard deviation is the sum of the weighted covariances.

$$E(R_p) = \sum_{i=1}^{N} x_i E(R_i) = \sum_{i=1}^{N} x_i \mu_i \tag{16}$$

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[18] The bias statistic shown is a statistical metric that is used to measure the accuracy of risk prediction; if the ex-ante risk prediction is unbiased, then the bias statistic should be close to 1.0. Clearly, the bias statistics obtained without the aid of the AAF methodology are significantly above the 95% confidence interval, which shows that the downward bias in the risk prediction of optimized portfolios is statistically significant. The AAF methodology recognizes the possibility of inadequate systematic risk estimation and guides the optimizer to avoid taking excessive unintended bets.

[19] Guerard. Markowitz, and Xu (2013 and 2015) created efficient frontiers using both of the Axioma Risk Models and found that the statistically-based Axioma Risk Model, the authors denoted as "STAT", produced higher geometric means, Sharpe ratios, and information ratios than the Axioma fundamental Risk Model, denoted as "FUND". The AAF technique was particularly useful with composite models of stock selection using fundamental data, momentum, and earnings expectations data. Furthermore, the geometric means and Sharpe ratios increase with the targeted tracking errors; however, the information ratios are higher in the lower tracking error range of 3–6%, with at least 200 stocks, on average, in the optimal portfolios. The Guerard et al. studies assumed 150 basis points, each way, of transactions costs. The use of ITG cost curves produced about 115-125 basis points of transactions costs, well under the assumed costs. The Guerard et al. studies also used the Sungard APT statistical model which produced statistical significant asset selection in U.S. and global portfolios.

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} x_i \, x_j c_{ij} \tag{17}$$

where μ is the expected return vector, C is the variance-covariance matrix, x is the portfolio weights.

The efficient frontier can be traced out by

$$minimize_{\{x_i \geq 0, x_i \leq \bar{u}\}} \;\; x^T Cx - \lambda \mu^T x \tag{18}$$

where λ is the risk-return tradeoff parameter and $\bar{u}$ is the fixed upper bound.

However, as the number of securities, N, increases, the number of variance-covariances increases faster, at being $N \times (N+1)/2$. This leads to estimate C by a factor model, in which the individual stock return R_j of security j at time t, dropping the subscript t for time, may be written like this:

$$R_j = \sum_{k=1}^{K} \beta_{jk} \widetilde{f_k} + \widetilde{e_j}. \tag{19}$$

The nonfactor, or asset-specific, return on security j, $\widetilde{e_j}$, is the residual risk of the security after removing the estimated impacts of the K factors.[20] The term f_k is the rate of return on factor k. The factor model simplifies the C as the sum of the systematic risk covariance and diagonal specific variances,

$$C = \beta C_{f,f} \beta' + \Sigma. \tag{20}$$

If the investor is more concerned about tracking a particular benchmark, the mean-variance optimization in Eq. (18) can be reformulated as a mean-variance tracking error at risk (MVTaR) optimization:

$$\text{minimize} \;\; (x - x_b)^T C (x - x_b) - \lambda \mu^T (x - x_b) \tag{21}$$

where x_b is the weight vector of the benchmark.

One can enhance the tracking by adding equal active weighing constraints (EAW):

$$|x_j - (x_b)_j| \leq y, \quad \text{for all } \; j \tag{22}$$

The MVTaR with constraints in Eq.(22) will be referred to as EAWTaR. The EAWTaR optimization technique enhances Information Ratios, relative to MVTaR, because it lowers realized tracking errors.[21] We believe that the EAWTaR optimization techniques creates portfolio that are consistent with the semi-variance and skewness applications.

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[20] The estimation of factors, or betas, can be accomplished using firm fundamental data, as in the Rosenberg (1974), Rosenberg and Marathe (1979), and Menchero et al. (2010), or principal component analysis of historical stock returns, as in Blin, Bender, and Guerard (1995), or Saxena and Stubbs (2012), or Guerard, Markowitz, and Xu (2014). The reader is referred to complete and excellent surveys of multi-factor models found in Rudd and Clasing (1982), Farrell (1997), Grinold and Kahn (1999), Haugen (2001), and Connor, Goldberg, and Korajczyk (2010).

[21] Markowitz reminds researchers that Chapter 9 of his seminal Portfolio Selection (1959) introduced the semi-variance to portfolio construction. Financial researchers, such as Konno, Pliska, and Suzuki (1993), Konno, Shirakawa, and Yamazaki (1993), King (1993), and Kijima and Ohnishi (1993), examined alternative risk modeling techniques, including the semi-variance, to enhance the risk-return trade-off.

30.5 HAS THE FINANCIAL WORLD CHANGED FROM 2003 (or 2010)? EMPIRICAL RESULTS

Global modeling for a "global growth specialist", such as McKinley Capital Management, LLC (2006a, b), involves the use of larger weighting of momentum and forecasted earnings acceleration factors. In this analysis, we report results for two universes: Russell 3000 Index stocks for U.S. stocks; and (2) the index constituents of the MSCI All Country World ex USA (ACWexUS) and EAFE Universes for international stocks. Our data source is the FactSet WorldScope database. The REG8, REG9CTEF, and REG10 models are estimated using the FactSet database for U.S. and All Country World Investable ex US and EAFE stocks for the 1997 – 2016 time period and subperiods. Moreover, we use the Beaton-Tukey bisquare procedure to estimate robust regression estimates of the models. We use latent root regression to address the issue of multicollinearity. The WLRR analysis is very similar to the Leamer Bayesian analysis of multicollinearity (1973 and 1978) and Lin, Foster, and Ungar (2011).

We create forecasted earnings acceleration growth variable and corporate exports variables. Our analysis is developed for the December 1996 – November 2016 period. Our simulation conditions assume 8 percent monthly turnover, 35 basis point threshold positions, an upper bound in mean-variance (MV) optimization of 4 percent on security weights, and ITG transactions costs[22].

Guerard et al. (2015) reported three levels of testing investment strategies.[23] In this analysis we restrict ourselves to levels I and II tests of Information Coefficients, ICs, Efficient Frontiers. We seek to maximize the Geometric Mean (GM), Information Ratios(IRs), and Sharpe Ratios (ShRs). In Sections 2 and 3, we traced the model development of CTEF, REG8, REG9CTEF, and REG10. We rank these variables, low to high, 99 is preferred, and we refer to ranked CTEF as CTEF (RCTEF). In the U.S. universe, using Russell 3000 stocks, we estimate REG10, known also as U.S. Expected Returns, or USER, see Guerard, Xu, and Gultekin (2012) and Guerard, Markowitz, and Xu (2014). If we examine the ICs over the December 1996 – November 2016, and its 15, 10, 5, 3, and one-year time sub-periods, we report in Exhibit 1 that ranked CTEF has the highest Information Coefficient among U.S. financial variables, in the 20-year time period as well as the 15-year, 10-year, 5-year, 3-year time periods, and is statistically significant in these time periods. The ranked CTEF is generally followed by REG9CTEF in most time periods which is almost always statistically significant. REG10 is most often third and REG8 is fourth in the U.S. The RCTEF, REG9CTEF, and USER quintile spreads approach 15 – 17 percent, annually, for 20 years. The ranked earnings-to-price, REP, and ranked book value-to-price, RBP, are included and are not generally statistically significant. See Exhibit 1. In terms of the top decile minus bottom decile spreads, REG10, REG9CTEF, and RCTEF, lead the variables, see Exhibit 1. How often should portfolios turnover? Bloch et al. (1993) argued for lower turnover to maximize the Geometric Mean. We agree! We report in Exhibit 2, that monthly turnover of 10 and 20 percent maximizes the Geometric Mean. TO (10) means 5% buys and 5% sells (or both way, round-trip turnover). Turnover exceeding 10% buys with our variables are ruinous. In Exhibit 3, we report monthly Axioma attribution statistics which, in the case of RCTEF, indicates that the forecasted earnings acceleration variable loads on Medium-Term Momentum (0.257), Growth (0.151), and Value (0.469). The Equally-weighted RCTEF, REG8, REG9CTEF, and REG10 portfolios produce approximately 300-350 basis points of Specific Returns for the 20-year time periods, see Exhibit 3. In the U.S. portfolios, equally-weighted 125

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[22] ITG estimate our transactions costs to be about 60 basis points, each-way, for 2011-2015.

[23] The first level is the information coefficient, IC, of a strategy in which the subsequent ranked returns are regressed as a function of the ranked financial strategy. The regression coefficient is the IC which is a randomly distributed variable to test the statistical significant of the individual variable or composite model strategies. The second level of investment testing is to estimate, with transactions costs, the Markowitz efficient frontier, by varying either the lambda or the targeted tracking error. The third level of testing is to apply the Markowitz and Xu (1994) Data Mining Corrections, DMC, to test whether the strategy is statistically different from any model that could have been used. Moreover, the regression coefficient of the DMC test indicates how much excess returns could be continued into the future, holding everything else constant.

stock portfolios outperform Mean-Variance (MV) four percent portfolios. [24] In a summary attribution analysis verification, Bijan Beheshti of FactSet worked with the authors to produce Axioma attribution analysis of these U.S. portfolios that report, in Exhibit 4, that the only ranked CTEF variable, RCTEF, produces statistically significant portfolio Active Total returns and Stock Specific Returns in the U.S. The REG8, REG9CTEF, and REG10 portfolios produce statistically significant portfolio Active Total returns but insignificant Stock Specific Returns for the 1/2003 -11/2016 time period.

In the Non-U.S. and EAFE universes, we estimate REG10, known also as Global Expected Returns when use all stocks in the world, or GLER, see Guerard, Markowitz, and Xu (2014) and Guerard, Markowitz, and Xu (2015). If we examine the ICs over the January 2002 – November 2016, and its 10, 5, 3, and one-year time sub-periods, we report in Exhibit 5 that ranked CTEF has the highest Information Coefficient among Non-U.S. financial variables. REG9CTEF and REG10 are statistically significant and only slightly less than RCTEF. The individual REP and RBP and forecasted one-year-ahead earnings yield, R_FEP1, are far less powerful. The RCTEF, REG9CTEF, and REG10 non-U.S. portfolios produce higher ICs, higher Quintile Spreads, see Exhibit 5. Non-US portfolio turnover are turnover-constrained, see Exhibit 6. The RCTEF, REG9CTEF, and REG10 produce approximately 400-500 basis points of Active Returns and about 250 basis points of Specific Returns, see Exhibit 7. The Non-U.S. portfolios offer more stock selection than U.S. portfolios with the addition of the REG8, REG9, and REG10 factors. The t-statistic on the risk stock selection effect in Non-U.S. portfolios is maximized with ranked CTEF, see Exhibit 8. The t-statistics on the risk stock selection effect is statistically significant for REG8, REG9CTEF, and REG10, although the t-statistic on the risk stock selection effect in the Non-U.S. portfolios is only statically significant at the 10 percent level. Exhibits 4 and 8 are most important for comparing U.S. and Non-U.S. portfolios. Only ranked CTEF is statistically significant in the U.S. whereas ranked CTEF, REG8, REG9CTEF, and REG10 are statistically significant in Total Active Returns and Risk Stock Selection Returns.

Before closing the discussion of Mean-Variance analysis, it is important to respond to Brennan and Lo (2012) whose article on portfolio optimization will be regarded as a modern classic. In a footnote, Brennan and Lo repeat comments of practitioners who claim the MV analysis produces absurd solutions. It is our experience, with our variables, that this is not a valid claim. A simple test was performed for the January 2003 – December 2016 time period. We produce monthly ranked CTEF variables for the Russell 3000 (R3) and World Investable ex US (XUS) index constituents. We prefer to but higher ranked stocks, 85-99, and sell those with lower scores, such as 70. [25] The R3 and XUS model correctly rank-order stocks; that is, to buy R3 stocks exceeding 85, hold them in equally-weighted portfolios until their monthly RCTEF score falls below 70, produced an annualized Active Return of 6.88%, composed of highly statistically significant stock selection (Specific Returns), see Exhibit 9. A similar test to buy XUS stocks exceeding 85, hold them in equally-weighted portfolios until their monthly RCTEF score falls below 70, produced annualized Active Returns of 98.15%, see Exhibit 9. We refer to the "buy, hold, sell" test as the Boolean Signal test. The Boolean Signal "buy at 85 and sell at 70" XUS and R3 portfolios are analyzed in the Axioma attribution system and produce highly statistically significant Active Returns and Specific Returns for the 2003 – 2016 period as well as the 2012 – 2016 post-Global Financial Crisis period. In fact, in the post-GFC time period, all ranked CTEF Active returns are Specific returns. In the 2003-2016 time period, all R3 ranked CTEF Active Returns (6.88%) are Specific Returns (7.24%); whereas the majority of Non-US ranked CTEF Active Returns (8.15%) are Specific Returns (5.02%). We believe that the Boolean Signal test confirms the validity of MV application.[26] The world is changing; but

[24] Levy and Duchin (2010) argued that if the ex ante pararmeter estimates are available, as they are to institutional investors, then the Markowitz Mean-Variance optimization is preferred; if not, then the Babylonian Talmud wise men theory of equally-weighted portfolios (their "1/N", N being the number of assets rule) conforms to a rationale investment strategies for individuals with a limited number of stocks held.

[25] The APT and Axioma optimizers generally sell stocks with CTEF scores less than 70.

[26] No transactions costs are included in the Boolean Signal analysis. Professor Andrew Lo agreed in private correspondence with the authors regarding our MV approach.

as bottom-up quantitative stock pickers, we report that MV models which were statistically significant for 1990 - 2001 in Guerard and Mark (2003) continue to be statistically significant in 1996 - 2106, 2003 – 2017, and the post-Global Financial Crisis period. Models cannot be perfect, but they can, and for practitioners, should be statistically significant. We have shown how forecasted earnings acceleration produces highly statistically significant stock selection in Non-US and U.S. stock universes. CTEF, REG8, REG9CTEF, and REG10 models optimized portfolios produce higher Active and Specific Returns in Non-U.S. stocks, whereas only CTEF works in U.S.

30.6 Summary and Conclusions

We report that a stock selection model and an earnings forecasting model which produce statistically significant asset selection in U. S. stocks, 1997-2016, Non-US stocks during the December 2002 – November 2016 period. We report two variations of Markowitz mean-variance optimization and equally-weighted techniques are particularly efficient for producing efficient frontiers. We show how forecasted earnings acceleration produces highly statistically significant stock selection in global and U.S. stock universes. CTEF, REG8, REG9CTEF, and REG10 models optimized portfolios produce higher Active and Specific Returns in Non-U.S. stocks, whereas only CTEF works in U.S. CTEF and PM complement the original eight-factor Markowitz Model in Non-U.S. stocks. Have markets and stock selection models changed since Guerard and Mark (2003)? CTEF, REG9CTEF, REG10 still dominate most other models, including the 36 models tested in Guerard, Gillam, Markowitz, Xu, and Wang (2018), including the Post-Global Financial Crisis. As we look ahead, extra earnings analysis, such as the information in earnings transcripts, Gillam, Guerard, and Cahan (2015) reported that earnings transcripts contain information that offers statistical support for inclusion in the portfolio creation process.

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Exhibit 1: Decile and Quintile Spreads, and Information Coefficients of U.S. Stocks

Frequency: Monthly
Average Monthly Returns * 12

Data - 10 Years or More

Model_Name	Period (Years)	D1 Return	D10 Return	Q1 Return	Q5 Return	D1-U	Q1-U	D1-D10	Q1-Q5	Q1 IR	T-Stat of Q1 IR	IC	T-Stat of IC	Start Date to 11/30/16
RBP	20	10.2	9.8	10.6	9.9	-1.2	-0.8	0.4	0.6	0.07	0.03	0.00	-0.62	12/31/96
RCTEF	20	20.3	4.7	18.6	5.2	9.0	7.3	15.5	13.4	1.09	0.88	0.05	7.68	12/31/96
REG10	20	18.7	-0.9	17.7	2.0	7.9	7.0	19.6	15.7	0.91	0.74	0.05	6.83	12/31/96
REG8	20	17.7	4.8	17.0	5.0	6.4	5.7	12.9	12.0	0.66	0.47	0.04	5.08	12/31/96
REG9CTEF	20	20.8	3.2	19.1	2.5	9.9	8.1	17.6	16.6	0.92	0.70	0.05	7.30	12/31/96
REP	20	13.4	9.3	13.8	9.4	1.1	1.5	4.1	4.4	0.41	0.28	0.03	4.62	12/31/96
RFEP1	20	17.4	5.8	17.6	6.7	5.9	6.0	11.6	10.9	0.68	0.46	0.05	5.70	12/31/96
RBP	15	11.1	9.7	11.1	10.1	-0.1	-0.1	1.3	1.1	0.17	0.07	0.00	-0.23	12/31/01
RCTEF	15	19.7	5.2	18.0	5.6	8.6	6.9	14.4	12.4	1.24	0.88	0.05	6.72	12/31/01
REG10	15	15.6	0.7	15.1	4.0	4.9	4.4	14.9	11.1	0.88	0.61	0.04	5.86	12/31/01
REG8	15	14.8	3.2	14.5	4.4	4.0	3.7	11.5	10.1	0.60	0.37	0.03	4.53	12/31/01
REG9CTEF	15	17.4	2.3	16.4	3.3	6.6	5.7	15.0	13.0	0.89	0.58	0.05	6.71	12/31/01
REP	15	13.0	9.9	12.2	10.1	1.3	0.6	3.1	2.1	0.43	0.27	0.03	3.81	12/31/01
RFEP1	15	16.8	8.1	16.2	6.7	5.7	5.1	8.7	9.5	0.72	0.43	0.05	5.73	12/31/01
RBP	10	9.0	8.3	9.9	8.9	-1.2	-0.3	0.7	1.0	0.09	0.03	0.00	-0.15	12/31/06
RCTEF	10	16.0	3.1	14.7	4.5	5.9	4.6	12.8	10.1	0.90	0.48	0.04	5.52	12/31/06
REG10	10	11.4	1.4	11.2	5.5	1.6	1.4	10.0	5.7	0.39	0.20	0.03	3.83	12/31/06
REG8	10	12.6	4.8	11.9	4.5	2.8	2.1	7.8	7.4	0.32	0.14	0.02	2.82	12/31/06
REG9CTEF	10	14.1	3.9	13.5	4.3	4.3	3.7	10.2	9.2	0.54	0.26	0.04	4.64	12/31/06
REP	10	11.1	9.5	10.5	9.6	0.9	0.3	1.6	0.9	0.22	0.11	0.02	2.81	12/31/06
RFEP1	10	13.8	6.5	13.0	6.7	3.9	3.0	7.3	6.3	0.40	0.17	0.04	4.60	12/31/06

Data – Less than 10 Years

Model_Name	Period (Years)	D1 Return	D10 Return	Q1 Return	Q5 Return	D1-U	Q1-U	D1-D10	Q1-Q5	Q1 IR	T-Stat of Q1 IR	IC	T-Stat of IC	Start Date to 11/30/16
RBP	5	11.1	14.2	11.6	15.4	-4.1	-3.6	-3.1	-3.8	-0.21	-0.08	0.00	-0.40	12/31/11
RCTEF	5	22.6	8.1	21.0	9.5	7.5	5.8	14.5	11.4	1.07	0.60	0.05	4.87	12/31/11
REG10	5	17.2	8.0	17.1	10.7	2.3	2.2	9.2	6.4	0.41	0.23	0.04	2.71	12/31/11
REG8	5	14.9	12.1	15.7	11.6	0.0	0.7	2.9	4.1	0.17	0.09	0.03	2.04	12/31/11
REG9CTEF	5	18.3	13.2	18.2	9.8	3.4	3.3	5.2	8.4	0.54	0.28	0.04	3.22	12/31/11
REP	5	14.5	14.8	15.1	14.8	-1.0	-0.4	-0.3	0.3	0.11	0.06	0.02	1.82	12/31/11
RFEP1	5	19.2	10.2	19.1	10.7	4.1	4.1	9.0	8.4	0.60	0.29	0.05	3.92	12/31/11
RBP	3	2.7	3.1	3.2	5.3	-4.9	-4.5	-0.4	-2.2	-0.37	-0.10	0.00	0.02	12/31/13
RCTEF	3	15.0	-2.7	13.9	0.2	7.5	6.4	17.7	13.7	0.73	0.30	0.06	4.15	12/31/13
REG10	3	9.7	-4.0	10.0	0.2	2.6	2.9	13.7	9.8	0.17	0.07	0.04	2.20	12/31/13
REG8	3	6.9	0.0	7.9	0.6	-0.2	0.8	6.8	7.3	-0.09	-0.03	0.03	1.44	12/31/13
REG9CTEF	3	10.9	2.1	11.0	-1.7	4.0	4.0	8.8	12.7	0.28	0.11	0.05	2.43	12/31/13
REP	3	5.6	4.7	6.7	5.4	-3.1	-2.0	0.9	1.3	-0.26	-0.10	0.03	1.76	12/31/13
RFEP1	3	9.2	-2.4	11.1	-1.4	2.1	4.0	11.6	12.5	0.27	0.09	0.06	2.95	12/31/13
RBP	1	29.1	12.1	24.5	13.0	7.9	3.3	17.1	11.5	0.65	0.08	0.03	1.37	12/31/15
RCTEF	1	25.6	17.4	24.1	17.8	5.2	3.6	8.3	6.2	1.49	0.30	0.03	1.54	12/31/15
REG10	1	23.3	-1.6	24.0	6.4	3.8	4.5	24.9	17.7	1.25	0.24	0.05	1.31	12/31/15
REG8	1	30.4	-9.0	27.6	0.5	11.4	8.6	39.3	27.1	1.52	0.27	0.07	1.89	12/31/15
REG9CTEF	1	29.5	0.7	28.7	0.3	10.5	9.7	28.8	28.5	1.65	0.30	0.07	2.05	12/31/15
REP	1	23.3	17.8	22.5	18.4	1.7	0.9	5.5	4.1	1.20	0.23	0.04	1.12	12/31/15
RFEP1	1	27.0	17.2	27.7	11.9	7.0	7.6	9.8	15.8	1.29	0.21	0.07	1.70	12/31/15

Exhibit 2: US Portfolio Statistics

RCTEF – JGAM 20 YR – Russell 3000; Equal Weighted; Includes Transaction Costs

$500mm, MV.25, #125, equal weight, min.10, no constraints
12/31/96 -12/31/2016
RCTEF

	Turnover							
	TO(200)	TO(100)	TO(80)	TO(60)	TO(40)	TO(30)	TO(20)	TO(10)
Sharpe Ratio	32%	32%	33%	37%	44%	49%	48%	50%
Information Ratio	**-0.228**	**-0.236**	**-0.217**	**-0.118**	**0.047**	**0.162**	**0.139**	**0.235**
Realized Standard Deviation	19%	19%	19%	19%	19%	19%	19%	19%
Realized Tracking Error	**7.7%**	**7.7%**	**7.6%**	**7.6%**	**7.2%**	**6.9%**	**6.9%**	**6.4%**
Annual Rate of Return	**6%**	**6%**	**6%**	**7%**	**8%**	**9%**	**9%**	**9%**
P/S Turnover	389%	384%	373%	334%	238%	177%	121%	66%
Turnover	792%	783%	759%	680%	487%	367%	256%	146%
Long Turnover	795%	786%	762%	683%	487%	367%	256%	149%
Short Turnover	3%	3%	3%	3%	0%	0%	0%	3%
Trade Win/Loss	0.575	0.5749	0.5754	0.5879	0.61	0.6343	0.6504	0.707
Total Return	2.2725	2.2342	2.3277	2.8428	3.8306	4.5802	4.4186	5.0013
Max Drawdown	0.6515	0.6513	0.6483	0.6399	0.6073	0.5983	0.6074	0.6145
Drawdown Detection Threshold	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Number of Drawdowns Over Threshold	14	14	13	16	16	19	16	17

REG9CTEF – JGAM 20 YR – Russell 3000; Equal Weighted; Includes Transaction Costs

$500mm, MV.25, #125, equal weight, min.10, no constraints
12/31/96 -12/31/2016
REG9CTEF

	Turnover							
	TO(200)	TO(100)	TO(80)	TO(60)	TO(40)	TO(30)	TO(20)	TO(10)
Sharpe Ratio	39%	39%	39%	40%	44%	49%	50%	53%
Information Ratio	**-0.068**	**-0.065**	**-0.066**	**-0.062**	**0.04**	**0.139**	**0.178**	**0.277**
Realized Standard Deviation	19%	19%	19%	19%	18%	18%	18%	18%
Realized Tracking Error	**7.6%**	**7.6%**	**7.5%**	**7.5%**	**7.3%**	**7.2%**	**7.0%**	**6.8%**
Annual Rate of Return	**7%**	**7%**	**7%**	**7%**	**8%**	**9%**	**9%**	**10%**
P/S Turnover	271%	271%	270%	264%	226%	177%	122%	67%
Turnover	555%	554%	553%	541%	464%	365%	257%	146%
Long Turnover	557%	557%	556%	544%	466%	365%	260%	149%
Short Turnover	3%	3%	3%	3%	3%	0%	3%	3%
Trade Win/Loss	0.5923	0.5926	0.5917	0.5926	0.6001	0.6134	0.6348	0.6837
Total Return	3.1224	3.1441	3.1352	3.1609	3.7949	4.45	4.7139	5.4276
Max Drawdown	0.64	0.6384	0.6388	0.6374	0.6125	0.5916	0.5927	0.5769
Drawdown Detection Threshold	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Number of Drawdowns Over Threshold	18	18	18	17	18	19	19	20

REG8 – JGAM 20 YR – Russell 3000; Equal Weighted; Includes Transaction Costs

$500mm, MV.25, #125, equal weight, min.10, no constraints
12/31/96 -12/31/2016
REG8

	Turnover							
	TO(200)	TO(100)	TO(80)	TO(60)	TO(40)	TO(30)	TO(20)	TO(10)
Sharpe Ratio	44%	44%	44%	44%	44%	44%	46%	56%
Information Ratio	**0.046**	**0.054**	**0.057**	**0.05**	**0.05**	**0.043**	**0.085**	**0.356**
Realized Standard Deviation	19%	19%	19%	19%	19%	19%	18%	18%
Realized Tracking Error	**7.5%**	**7.5%**	**7.5%**	**7.5%**	**7.5%**	**7.3%**	**7.1%**	**6.7%**
Annual Rate of Return	**8%**	**8%**	**8%**	**8%**	**8%**	**8%**	**8%**	**10%**
P/S Turnover	192%	192%	191%	191%	183%	164%	122%	64%
Turnover	397%	397%	396%	395%	379%	341%	257%	142%
Long Turnover	397%	397%	396%	395%	379%	341%	257%	142%
Short Turnover	0%	0%	0%	0%	0%	0%	0%	0%
Trade Win/Loss	0.6026	0.6031	0.6033	0.6039	0.6051	0.6085	0.6201	0.6778
Total Return	3.8356	3.8905	3.9115	3.8633	3.865	3.8115	4.075	6.0512
Max Drawdown	0.6102	0.6096	0.6093	0.6124	0.6147	0.6099	0.6003	0.5703
Drawdown Detection Threshold	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Number of Drawdowns Over Threshold	19	19	19	19	19	19	20	20

REG10 – JGAM 20 YR – Russell 3000; Equal Weighted; Includes Transaction Costs

$500mm, MV.25, #125, equal weight, min.10, no constraints
12/31/96 -12/31/2016
REG10

	Turnover							
	TO(200)	TO(100)	TO(80)	TO(60)	TO(40)	TO(30)	TO(20)	TO(10)
Sharpe Ratio	36%	35%	35%	36%	42%	45%	50%	56%
Information Ratio	**-0.197**	**-0.199**	**-0.198**	**-0.186**	**-0.038**	**0.03**	**0.157**	**0.334**
Realized Standard Deviation	18%	18%	18%	18%	18%	18%	18%	18%
Realized Tracking Error	**7.2%**	**7.2%**	**7.2%**	**7.1%**	**6.9%**	**6.7%**	**6.6%**	**6.3%**
Annual Rate of Return	**6%**	**6%**	**6%**	**7%**	**8%**	**8%**	**9%**	**10%**
P/S Turnover	310%	310%	309%	297%	231%	177%	121%	64%
Turnover	634%	634%	632%	608%	476%	367%	257%	143%
Long Turnover	634%	634%	632%	608%	476%	367%	259%	143%
Short Turnover	0%	0%	0%	0%	0%	0%	3%	0%
Trade Win/Loss	0.5852	0.5852	0.5865	0.5868	0.5999	0.6119	0.639	0.7004
Total Return	2.4816	2.4713	2.4768	2.5434	3.3231	3.7106	4.5017	5.6859
Max Drawdown	0.6335	0.6339	0.6334	0.6313	0.6155	0.5967	0.5815	0.5375
Drawdown Detection Threshold	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Number of Drawdowns Over Threshold	14	13	14	14	16	18	21	23

RCTEF – JGAM 20 YR – Russell 3000; Equal Weighted; +/- 4%; Includes Transaction Costs

$500mm, MV.25, #125, equal weight, min.10, no constraints
12/31/96 -12/31/2016
RCTEF **Turnover**

	TO(200)	T0(100)	TO(80)	TO(60)	TO(40)	TO(30)	TO(20)	TO(10)
Sharpe Ratio	29%	30%	31%	35%	41%	46%	51%	54%
Information Ratio	**-0.316**	**-0.294**	**-0.269**	**-0.187**	**-0.032**	**0.09**	**0.206**	**0.297**
Realized Standard Deviation	19%	19%	19%	18%	18%	18%	18%	19%
Realized Tracking Error	**7.7%**	**7.6%**	**7.6%**	**7.5%**	**7.4%**	**7.2%**	**7.1%**	**7.0%**
Annual Rate of Return	**5%**	**6%**	**6%**	**6%**	**8%**	**9%**	**9%**	**10%**
P/S Turnover	406%	396%	381%	336%	237%	177%	122%	66%
Turnover	826%	807%	777%	684%	486%	367%	257%	147%
Long Turnover	826%	807%	777%	684%	486%	367%	257%	147%
Short Turnover	0%	0%	0%	0%	0%	0%	0%	0%
Trade Win/Loss	0.5549	0.556	0.5574	0.5599	0.5711	0.5749	0.588	0.6171
Total Return	1.8822	1.9788	2.0927	2.4892	3.342	4.1185	4.9475	5.6304
Max Drawdown	0.622	0.6206	0.6186	0.6116	0.5993	0.5962	0.5967	0.5881
Drawdown Detection Threshold	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Number of Drawdowns Over Threshold	14	14	14	15	17	17	18	17

REG9CTEF – JGAM 20 YR – Russell 3000; Equal Weighted; +/- 4%; Includes Transaction Costs

$500mm, MV.25, #125, equal weight, min.10, no constraints
12/31/96 -12/31/2016
REG9CTEF **Turnover**

	TO(200)	T0(100)	TO(80)	TO(60)	TO(40)	TO(30)	TO(20)	TO(10)
Sharpe Ratio	40%	40%	40%	40%	42%	43%	47%	51%
Information Ratio	**-0.077**	**-0.079**	**-0.077**	**-0.069**	**-0.04**	**-0.004**	**0.083**	**0.201**
Realized Standard Deviation	18%	18%	18%	18%	18%	18%	18%	18%
Realized Tracking Error	**7.8%**	**7.8%**	**7.7%**	**7.7%**	**7.6%**	**7.5%**	**7.3%**	**7.1%**
Annual Rate of Return	**7%**	**7%**	**7%**	**7%**	**8%**	**8%**	**8%**	**9%**
P/S Turnover	273%	273%	271%	265%	227%	177%	122%	67%
Turnover	558%	557%	554%	540%	464%	365%	256%	146%
Long Turnover	558%	557%	554%	540%	464%	365%	256%	146%
Short Turnover	0%	0%	0%	0%	0%	0%	0%	0%
Trade Win/Loss	0.573	0.5736	0.5734	0.5745	0.5758	0.5868	0.6063	0.6452
Total Return	3.0625	3.0488	3.0616	3.1097	3.2891	3.5104	4.0743	4.8959
Max Drawdown	0.6054	0.6055	0.6053	0.6005	0.5852	0.5898	0.5773	0.564
Drawdown Detection Threshold	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Number of Drawdowns Over Threshold	18	18	18	18	18	19	19	19

REG8 – JGAM 20 YR – Russell 3000; Equal Weighted; +/- 4%; Includes Transaction Costs

$500mm, MV.25, #125, equal weight, min.10, no constraints
12/31/96 -12/31/2016
REG8 **Turnover**

	TO(200)	T0(100)	TO(80)	TO(60)	TO(40)	TO(30)	TO(20)	TO(10)
Sharpe Ratio	47%	47%	47%	47%	47%	47%	48%	53%
Information Ratio	**0.105**	**0.107**	**0.107**	**0.108**	**0.106**	**0.103**	**0.131**	**0.264**
Realized Standard Deviation	18%	18%	18%	18%	18%	18%	18%	18%
Realized Tracking Error	**7.7%**	**7.7%**	**7.7%**	**7.7%**	**7.7%**	**7.6%**	**7.4%**	**7.2%**
Annual Rate of Return	**9%**	**9%**	**9%**	**9%**	**9%**	**9%**	**9%**	**10%**
P/S Turnover	192%	192%	192%	190%	182%	162%	122%	66%
Turnover	398%	397%	397%	394%	375%	337%	257%	148%
Long Turnover	398%	397%	397%	394%	375%	337%	257%	157%
Short Turnover	0%	0%	0%	0%	0%	0%	0%	9%
Trade Win/Loss	0.5946	0.5961	0.5965	0.5958	0.5954	0.6017	0.6117	0.6478
Total Return	4.2664	4.2863	4.281	4.2887	4.2763	4.247	4.43	5.4394
Max Drawdown	0.5906	0.5904	0.5905	0.5909	0.5912	0.5912	0.5946	0.5976
Drawdown Detection Threshold	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Number of Drawdowns Over Threshold	21	22	21	21	21	21	22	21

REG10 – JGAM 20 YR – Russell 3000; Equal Weighted; +/- 4%; Includes Transaction Costs

$500mm, MV.25, #125, equal weight, min.10, no constraints
12/31/96 -12/31/2016
REG10 **Turnover**

	TO(200)	T0(100)	TO(80)	TO(60)	TO(40)	TO(30)	TO(20)	TO(10)
Sharpe Ratio	34%	35%	35%	35%	39%	44%	50%	51%
Information Ratio	**-0.233**	**-0.228**	**-0.226**	**-0.213**	**-0.127**	**-0.014**	**0.136**	**0.2**
Realized Standard Deviation	18%	18%	18%	18%	18%	18%	18%	18%
Realized Tracking Error	**7.4%**	**7.4%**	**7.4%**	**7.4%**	**7.2%**	**7.0%**	**6.9%**	**6.9%**
Annual Rate of Return	**6%**	**6%**	**6%**	**6%**	**7%**	**8%**	**9%**	**9%**
P/S Turnover	312%	311%	310%	295%	231%	176%	121%	66%
Turnover	638%	638%	634%	605%	476%	367%	256%	148%
Long Turnover	638%	638%	634%	605%	476%	367%	256%	157%
Short Turnover	0%	0%	0%	0%	0%	0%	0%	9%
Trade Win/Loss	0.5596	0.5601	0.5612	0.5606	0.5705	0.5791	0.5949	0.637
Total Return	2.2829	2.3047	2.3144	2.3863	2.8286	3.4578	4.3915	4.8448
Max Drawdown	0.625	0.6239	0.6245	0.6222	0.6056	0.5932	0.5679	0.5949
Drawdown Detection Threshold	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Number of Drawdowns Over Threshold	16	16	16	16	18	20	24	25

Exhibit 3: U.S. Portfolio Attributions

JGAM 20 YR – Russell 3000; Equal Weighted

		RCTEF			REG8			REG9CTEF			REG10	
Row Labels	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error
Factor		5.57%	4.34%		-4.51%	4.89%		3.26%	4.56%		5.07%	4.31%
Industry	-0.003	0.00%	2.02%	-0.004	0.00%	2.28%	-0.003	0.00%	2.36%	-0.004	0.00%	2.28%
Style	0.625	7.23%	3.80%	0.364	1.73%	4.28%	0.399	6.12%	3.84%	0.465	6.88%	3.59%
Dividend Yield	0.017	-0.06%	0.04%	0.302	0.64%	0.13%	0.170	0.60%	0.04%	0.142	0.39%	0.03%
Exchange Rate Sensitivity	0.020	0.70%	0.04%	-0.005	-0.12%	0.06%	-0.008	0.17%	0.07%	-0.009	0.43%	0.06%
Growth	0.169	-0.01%	0.09%	-0.018	-0.10%	0.07%	0.069	0.20%	-0.05%	0.072	0.18%	-0.01%
Leverage	0.164	-1.04%	0.19%	0.081	-0.86%	0.17%	0.046	-0.58%	0.13%	0.026	-0.33%	0.15%
Liquidity	0.083	0.13%	-0.28%	0.187	0.32%	-0.57%	0.131	0.54%	-0.53%	0.130	0.39%	-0.54%
Market Sensitivity	-0.147	3.62%	1.35%	-0.195	3.43%	1.28%	-0.185	3.67%	1.39%	-0.187	3.44%	1.48%
Medium-Term Momentum	0.239	3.13%	0.63%	-0.343	0.00%	1.38%	-0.146	0.00%	0.79%	0.059	-0.46%	0.33%
Return-on-Equity	0.037	0.95%	0.11%	-0.163	-6.53%	0.17%	-0.093	-2.58%	0.06%	-0.090	-2.08%	0.06%
Size	-0.533	1.46%	3.32%	-0.521	0.63%	3.38%	-0.478	0.98%	3.13%	-0.465	1.09%	3.01%
Value	0.462	5.48%	0.29%	0.924	6.85%	1.37%	0.835	6.83%	1.15%	0.745	6.06%	0.86%
Volatility	0.114	-3.98%	-0.23%	0.114	-4.49%	-0.27%	0.059	-0.23%	-0.13%	0.043	0.44%	-0.09%
Market	-0.003	1.81%	0.17%	-0.004	0.98%	0.15%	-0.003	1.43%	0.16%	-0.004	1.39%	0.20%
Market Intercept	-0.003	1.81%	0.17%	-0.004	0.98%	0.15%	-0.003	1.43%	0.16%	-0.004	1.39%	0.20%
Stock Specific		3.45%	2.75%		3.94%	2.77%		3.49%	2.65%		2.48%	2.61%

JGAM 15 YR – Russell 3000; Equal Weighted

		RCTEF			REG8			REG9CTEF			REG10 4.0	
Row Labels	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error
Factor		6.03%	3.80%		2.98%	3.93%		4.72%	3.67%		4.76%	3.48%
Industry	-0.004	0.00%	1.84%	-0.005	0.00%	1.96%	-0.004	0.00%	2.09%	-0.005	0.00%	2.19%
Style	0.700	6.65%	3.28%	0.427	4.25%	3.36%	0.416	6.02%	2.97%	0.495	6.35%	2.62%
Dividend Yield	-0.007	0.16%	0.13%	0.205	0.19%	0.12%	0.080	0.27%	0.10%	0.089	0.33%	0.11%
Exchange Rate Sensitivity	-0.004	0.02%	0.09%	-0.010	-0.12%	0.11%	-0.022	-0.05%	0.11%	-0.021	0.04%	0.11%
Growth	0.211	0.42%	0.10%	0.031	-0.04%	-0.05%	0.111	0.27%	-0.13%	0.115	0.23%	-0.01%
Leverage	0.152	-0.57%	0.12%	0.023	-0.24%	0.05%	-0.016	-0.06%	-0.01%	-0.072	0.06%	0.10%
Liquidity	0.092	0.47%	-0.24%	0.195	0.27%	-0.42%	0.138	0.36%	-0.43%	0.096	0.30%	-0.29%
Market Sensitivity	-0.122	1.40%	1.18%	-0.144	1.53%	0.86%	-0.142	1.76%	1.02%	-0.190	1.81%	1.45%
Medium-Term Momentum	0.274	2.54%	0.66%	-0.299	-2.60%	0.92%	-0.117	-1.00%	0.44%	0.095	0.39%	0.17%
Return-on-Equity	0.049	0.78%	0.11%	-0.110	-1.35%	0.13%	-0.069	-0.90%	0.05%	-0.062	-0.59%	0.02%
Size	-0.515	4.22%	2.82%	-0.486	3.57%	2.66%	-0.436	3.40%	2.42%	-0.327	2.44%	1.84%
Value	0.426	3.19%	0.21%	0.889	4.43%	1.30%	0.806	4.47%	1.08%	0.749	3.86%	0.76%
Volatility	0.145	-6.01%	-0.24%	0.134	-3.54%	-0.19%	0.083	-1.86%	-0.20%	0.024	-0.29%	-0.10%
Market	-0.004	1.15%	0.24%	-0.005	0.30%	0.24%	-0.004	0.78%	0.24%	-0.005	0.68%	0.31%
Market Intercept	-0.004	1.15%	0.24%	-0.005	0.30%	0.24%	-0.004	0.78%	0.24%	-0.005	0.68%	0.31%
Stock Specific		2.44%	2.42%		0.70%	2.37%		0.53%	2.26%		-2.46%	2.61%

JGAM 20 YR – Russell 3000; Equal Weighted; +/- 4%

		RCTEF 4.0			REG8 4.0			REG9CTEF 4.0			REG10 4.0	
Row Labels	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error
Factor		1.83%	4.06%		1.27%	4.69%		4.46%	4.41%		5.72%	4.16%
Industry	-0.010	2.49%	2.34%	-0.003	0.00%	2.42%	-0.003	0.00%	2.54%	-0.004	0.00%	2.45%
Style	0.862	0.00%	3.19%	0.458	3.67%	3.95%	0.474	6.42%	3.53%	0.534	7.14%	3.28%
Dividend Yield	0.095	1.26%	-0.02%	0.356	0.83%	0.16%	0.229	0.84%	0.09%	0.179	0.78%	0.06%
Exchange Rate Sensitivity	0.000	-1.42%	0.05%	-0.004	0.02%	0.05%	-0.020	0.21%	0.04%	-0.004	0.42%	0.06%
Growth	0.151	-1.67%	0.14%	-0.014	-0.01%	0.11%	0.074	0.27%	-0.04%	0.073	0.23%	0.02%
Leverage	0.163	1.21%	0.25%	0.086	-0.88%	0.19%	0.043	-0.39%	0.15%	0.012	-0.34%	0.19%
Liquidity	0.156	1.79%	-0.49%	0.155	0.15%	-0.51%	0.103	0.44%	-0.43%	0.100	0.33%	-0.43%
Market Sensitivity	-0.152	0.00%	1.48%	-0.222	3.53%	1.54%	-0.217	3.44%	1.61%	-0.220	3.38%	1.70%
Medium-Term Momentum	0.257	5.04%	0.75%	-0.327	0.00%	1.30%	-0.135	-9.00%	0.72%	0.074	-0.03%	0.31%
Return-on-Equity	0.082	1.60%	0.20%	-0.152	-5.31%	0.12%	-0.077	-1.75%	0.05%	-0.079	-1.54%	0.02%
Size	-0.382	0.00%	2.46%	-0.434	0.57%	2.88%	-0.387	0.95%	2.61%	-0.369	1.04%	2.45%
Value	0.469	8.36%	0.32%	0.953	6.92%	1.38%	0.847	6.34%	1.14%	0.761	5.72%	0.87%
Volatility	0.023	1.69%	0.01%	0.062	-1.32%	-0.26%	0.015	0.83%	-0.02%	0.006	1.26%	0.05%
Market	-0.010	2.16%	0.37%	-0.003	1.28%	0.18%	-0.003	1.09%	0.20%	-0.004	1.26%	0.23%
Market Intercept	-0.010	2.16%	0.37%	-0.003	1.28%	0.18%	-0.003	1.09%	0.20%	-0.004	1.26%	0.23%
Stock Specific			3.02%		3.56%	3.24%		1.71%	3.09%		1.35%	3.00%

JGAM 15 YR – Russell 3000; Equal Weighted; +/-4%

		RCTEF 4.0			REG8 4.0			REG9CTEF 4.0			REG10 4.0	
Row Labels	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error	Active Exposure	Active Return*	Tracking Error
Factor		1.40%	3.51%		3.91%	3.80%		4.83%	3.58%		4.76%	3.48%
Industry	-0.007	2.24%	24.40%	-0.005	0.00%	2.11%	-0.005	0.00%	2.26%	-0.005	0.00%	2.19%
Style	0.957	-6.72%	2.69%	0.469	5.06%	3.10%	0.421	6.23%	2.71%	0.495	6.35%	2.62%
Dividend Yield	0.062	-0.34%	0.08%	0.253	0.34%	0.14%	0.127	0.49%	0.11%	0.089	0.33%	0.11%
Exchange Rate Sensitivity	-0.026	-0.27%	0.12%	-0.014	-0.08%	0.10%	-0.038	-0.05%	0.07%	-0.021	0.04%	0.11%
Growth	0.203	-2.16%	0.16%	0.034	0.00%	0.00%	0.109	0.20%	-0.07%	0.115	0.23%	-0.01%
Leverage	0.148	-0.08%	0.20%	0.025	-0.27%	0.07%	-0.040	0.06%	0.01%	-0.072	0.06%	0.10%
Liquidity	0.168	-0.71%	-0.39%	0.153	0.21%	-0.34%	0.098	0.33%	-0.29%	0.096	0.30%	-0.29%
Market Sensitivity	-0.127	-3.77%	1.34%	-0.185	1.83%	1.21%	-0.185	1.90%	1.32%	-0.190	1.81%	1.45%
Medium-Term Momentum	0.296	3.35%	0.79%	-0.290	-2.59%	0.88%	-0.106	-0.94%	0.37%	0.095	0.39%	0.17%
Return-on-Equity	0.101	1.98%	0.24%	-0.105	-1.17%	0.09%	-0.054	-0.62%	0.05%	-0.062	-0.59%	0.02%
Size	-0.347	0.00%	1.94%	-0.395	2.98%	2.19%	-0.339	2.64%	1.92%	-0.327	2.44%	1.84%
Value	0.430	6.64%	0.18%	0.917	4.54%	1.28%	0.817	4.18%	1.04%	0.749	3.86%	0.76%
Volatility	0.049	0.28%	-0.15%	0.077	-1.41%	-0.26%	0.031	-0.32%	-0.14%	0.024	-0.29%	-0.10%
Market	-0.007	1.38%	0.38%	-0.005	0.51%	0.28%	-0.005	0.63%	0.30%	-0.005	0.68%	0.31%
Market Intercept	-0.007	1.38%	0.38%	-0.005	0.51%	0.28%	-0.005	0.63%	0.30%	-0.005	0.68%	0.31%
Stock Specific		0.00%	2.68%		-0.92%	2.84%		-1.83%	2.69%		-2.46%	2.61%

Exhibit 4: US Portfolios Attribution Summary

		Portfolio	REG10_NC	REG10_NC_4	REG9_CTEF_NC	REG9_CTEF_NC_4	REG8_NC	REG8_NC_4	RCTEF_NC	RCTEF_NC_4
		Port. Total Return	14.41	13.98	14.15	13.68	13.96	13.76	15.59	15.69
		Bench. Total Return	7.92	7.92	7.92	7.92	7.92	7.92	7.92	7.92
		Active Total Return	6.49	6.06	6.23	5.76	6.04	5.83	7.67	7.77
Risk Attribution		Factors Effect	6.44	6.22	5.78	6.28	5.08	5.32	5.91	5.02
		Risk Factors Effect T-Stat	5.16	5.31	4.51	4.76	4.04	3.83	5.76	4.91
		Stock Specific Effect	0.05	-0.16	0.45	-0.52	0.96	0.52	1.76	2.75
		Risk Stock Specific Effect T-Stat	0.71	0.22	0.96	0.25	1.20	1.27	2.41	2.62
		Total Effect	6.49	6.06	6.23	5.76	6.04	5.83	7.67	7.77
	Market	Compounded Factor Impact	-0.05	-0.04	-0.08	-0.06	-0.09	-0.09	-0.12	-0.06
		Factor Impact T-Stat	-0.44	-0.47	-0.61	-0.53	-0.64	-0.58	-0.77	-0.50
	Dividend Yield	Compounded Factor Impact	-0.04	-0.04	0.08	0.13	0.04	0.05	0.05	0.08
		Factor Impact T-Stat	-0.30	0.05	0.93	1.37	0.64	0.59	0.44	0.47
	Earnings Yield	Compounded Factor Impact	1.89	1.93	1.90	2.03	1.45	1.62	1.51	1.44
		Factor Impact T-Stat	7.26	6.75	6.90	6.64	6.60	6.36	6.25	5.75
	Exchange Rate Sensitivity	Compounded Factor Impact	0.05	0.04	0.02	-0.01	0.02	0.00	0.05	0.07
		Factor Impact T-Stat	0.78	0.99	0.23	0.04	-0.00	-0.07	1.17	1.09
	Growth	Compounded Factor Impact	0.02	0.03	0.01	-0.00	0.01	0.06	-0.02	-0.05
		Factor Impact T-Stat	0.77	0.89	0.56	0.50	0.52	0.95	-0.21	-0.53
	Leverage	Compounded Factor Impact	0.15	0.21	0.13	0.21	0.10	0.16	-0.01	0.04
		Factor Impact T-Stat	1.46	1.27	1.07	1.47	0.71	0.81	0.30	0.73
	Liquidity	Compounded Factor Impact	0.30	0.35	0.22	0.30	0.14	0.22	0.27	0.21
		Factor Impact T-Stat	6.09	3.96	6.02	5.26	3.20	2.80	5.30	3.76
	Market Sensitivity	Compounded Factor Impact	1.39	1.49	1.23	1.42	1.38	1.44	0.87	0.96
		Factor Impact T-Stat	2.60	2.44	2.43	2.32	2.86	2.35	2.43	2.19
	Medium-Term Momentum	Compounded Factor Impact	0.03	0.07	-0.49	-0.41	-0.68	-0.80	0.87	0.72
		Factor Impact T-Stat	0.29	0.61	-1.88	-1.67	-2.54	-2.60	2.47	1.70
	MidCap	Compounded Factor Impact	-0.37	-0.36	-0.35	-0.34	-0.37	-0.34	-0.34	-0.24
		Factor Impact T-Stat	-2.74	-3.02	-2.51	-2.82	-3.23	-3.23	-3.42	-3.21
	Profitability	Compounded Factor Impact	-0.19	-0.25	-0.26	-0.33	-0.32	-0.41	-0.18	-0.43
		Factor Impact T-Stat	-2.82	-3.44	-4.51	-4.99	-6.08	-7.13	-4.34	-7.41
	Size	Compounded Factor Impact	4.69	3.91	4.37	3.96	4.17	3.96	3.61	2.93
		Factor Impact T-Stat	5.27	5.62	5.21	5.59	5.17	5.40	5.42	5.60
	Value	Compounded Factor Impact	1.04	0.98	1.03	1.10	1.16	1.24	0.42	0.34
		Factor Impact T-Stat	5.35	4.95	4.75	4.94	4.54	4.60	5.26	5.59
	Volatility	Compounded Factor Impact	-0.91	-0.51	-0.92	-0.43	-0.90	-0.54	-0.72	-0.61
		Factor Impact T-Stat	-4.13	-2.40	-4.60	-1.92	-4.02	-1.78	-4.52	-2.94
	Industries	Compounded Factor Impact	-1.56	-1.60	-1.10	-1.29	-1.04	-1.26	-0.36	-0.37
		Factor Impact T-Stat	-1.86	-1.56	-1.69	-1.68	-1.50	-1.81	-0.69	-0.38

Exhibit 5: Quintile Spreads, and Information Coefficients of Non-US Stocks

Frequency: Monthly
Average Monthly Returns * 12

Model_Name	Period (Years)	Universe	U Return	Q1-U	Q1-Q5	Q1 IR	T-Stat of Q1 IR	IC	T-Stat of IC	Q1 % Frac. > Univ	Start Date
RCTEF	17	ACWI ex us	11.3	7.4	14.4	0.90	0.57	**0.050**	**8.26**	68.7	1/31/02
REG9CTEF	17	ACWI ex us	10.1	7.9	16.3	0.84	0.52	**0.046**	**7.96**	69.3	1/31/02
REG10	17	ACWI ex us	10.0	6.8	14.2	0.83	0.55	**0.042**	**7.42**	67.6	1/31/02
RFEP1	17	ACWI ex us	10.6	6.7	12.8	0.68	0.36	0.035	**4.28**	56.4	1/31/02
REG8	17	ACWI ex us	10.4	4.9	11.4	0.73	0.46	0.027	**4.05**	58.7	1/31/02
REP	17	ACWI ex us	11.5	1.3	3.3	0.59	0.36	0.012	**2.35**	50.3	1/31/02
RBP	17	ACWI ex us	11.5	-0.8	-1.8	0.40	0.20	-0.013	-1.37	43.6	1/31/02
RCTEF	15	ACWI ex us	11.3	7.4	14.4	0.90	0.57	**0.050**	**8.26**	68.7	1/31/02
REG9CTEF	15	ACWI ex us	10.1	7.9	16.3	0.84	0.52	**0.046**	**7.96**	69.3	1/31/02
REG10	15	ACWI ex us	10.0	6.8	14.2	0.83	0.55	**0.042**	**7.42**	67.6	1/31/02
RFEP1	15	ACWI ex us	10.6	6.7	12.8	0.68	0.36	0.035	**4.28**	56.4	1/31/02
REG8	15	ACWI ex us	10.4	4.9	11.4	0.73	0.46	0.027	**4.05**	58.7	1/31/02
REP	15	ACWI ex us	11.5	1.3	3.3	0.59	0.36	0.012	**2.35**	50.3	1/31/02
RBP	15	ACWI ex us	11.5	-0.8	-1.8	0.40	0.20	-0.013	-1.37	43.6	1/31/02
RCTEF	10	ACWI ex us	5.1	4.7	10.4	0.43	0.21	0.039	**5.51**	63.3	12/31/06
REG9CTEF	10	ACWI ex us	4.2	5.1	12.6	0.39	0.18	0.031	**4.23**	61.7	12/31/06
REG10	10	ACWI ex us	4.0	3.8	9.9	0.36	0.18	0.027	**3.95**	58.3	12/31/06
RFEP1	10	ACWI ex us	4.2	4.2	10.2	0.30	0.12	0.020	**1.96**	50.8	12/31/06
REG8	10	ACWI ex us	4.4	3.1	8.9	0.32	0.15	0.015	1.65	50.8	12/31/06
REP	10	ACWI ex us	5.4	1.0	3.6	0.26	0.12	0.011	1.60	46.7	12/31/06
RBP	10	ACWI ex us	5.5	0.3	1.0	0.20	0.08	-0.011	-0.88	45.8	12/31/06
RCTEF	3	ACWI ex us	1.0	6.0	13.9	0.50	0.21	**0.053**	**4.33**	66.7	12/31/13
REG9CTEF	3	ACWI ex us	-0.8	4.5	13.5	0.23	0.09	0.034	**2.17**	55.6	12/31/13
REG10	3	ACWI ex us	-0.3	4.2	10.2	0.27	0.12	0.026	**1.97**	61.1	12/31/13
REP	3	ACWI ex us	0.9	1.8	4.2	0.17	0.06	0.016	1.34	47.2	12/31/13
RFEP1	3	ACWI ex us	-0.9	3.8	11.7	0.17	0.06	0.017	0.88	50.0	12/31/13
REG8	3	ACWI ex us	-0.2	1.6	6.8	0.09	0.03	0.010	0.57	44.4	12/31/13
RBP	3	ACWI ex us	0.7	-1.0	0.1	-0.01	0.00	-0.011	-0.47	50.0	12/31/13
REG9CTEF	1	ACWI ex us	6.9	8.6	19.5	0.93	0.20	**0.067**	**2.26**	58.3	12/31/15
RBP	1	ACWI ex us	9.3	16.8	27.1	1.28	0.22	**0.068**	**2.05**	83.3	12/31/15
REG8	1	ACWI ex us	6.2	9.1	22.5	0.89	0.18	**0.062**	1.87	58.3	12/31/15
REG10	1	ACWI ex us	8.2	7.5	10.1	1.01	0.23	**0.051**	1.86	75.0	12/31/15
RFEP1	1	ACWI ex us	10.2	6.3	-0.9	0.94	0.18	**0.050**	1.23	50.0	12/31/15
REP	1	ACWI ex us	9.3	4.9	1.9	0.80	0.16	0.020	1.04	58.3	12/31/15
RCTEF	1	ACWI ex us	9.2	3.4	4.1	0.81	0.18	0.017	0.97	58.3	12/31/15

Exhibit 6: Non-US Portfolio Statistics

INTL JGAM 20 YR – ACWI x US; Equal Weighted; Includes Transaction Costs

	INTL RCTEF		INTL REG9CTEF		INTL REG8		INTL REG 10	
	TO(20)	ACWI ex US	TO(20)	ACWI ex US	TO(20)	ACWI ex US	TO(20)	ACWI ex US
Sharpe Ratio	72%	38%	72%	38%	57%	38%	71%	38%
Information Ratio	**0.784**		**0.827**		**0.421**		**0.77**	
Realized Standard Deviation	14%	16%	14%	16%	15%	16%	14%	16%
Realized Tracking Error	**5.3%**		**5.0%**		**5.1%**		**5.0%**	
Annual Rate of Return	**10%**	**6%**	**10%**	**6%**	**8%**	**6%**	**10%**	**6%**
P/S Turnover	120%		120%		119%		121%	
Turnover	260%		263%		264%		261%	
Long Turnover	260%		263%		264%		261%	
Short Turnover	0%		0%		0%		0%	
Trade Win/Loss	0.6444		0.6051		0.595		0.6261	
Total Return	3.3841	1.4595	3.3536	1.4595	2.3069	1.4595	3.1825	1.4595
Max Drawdown	0.6462	0.6083	0.6149	0.6083	0.5956	0.6083	0.6193	0.6083
Drawdown Detection Threshold	0.05		0.05		0.05		0.05	
Number of Drawdowns Over Threshold	8	10	8	10	7	10	9	10

INTL JGAM 20 YR – ACWI x US; Equal Weighted; +/- 4%; Includes Transaction Costs

	INTL RCTEF		INTL REG9CTEF		INTL REG8		INTL REG 10	
	TO(20)	ACWI ex US	TO(20)	ACWI ex US	TO(20)	ACWI ex US	TO(20)	ACWI ex US
Sharpe Ratio	79%	38%	73%	38%	59%	38%	70%	38%
Information Ratio	**0.86**		**0.863**		**0.489**		**0.731**	
Realized Standard Deviation	14%	16%	15%	16%	15%	16%	14%	16%
Realized Tracking Error	**5.8%**		**5.2%**		**5.4%**		**5.2%**	
Annual Rate of Return	**11%**	**6%**	**11%**	**6%**	**9%**	**6%**	**10%**	**6%**
P/S Turnover	120%		120%		120%		120%	
Turnover	261%		261%		262%		259%	
Long Turnover	261%		261%		262%		259%	
Short Turnover	0%		0%		0%		0%	
Trade Win/Loss	0.6135		0.6079		0.6089		0.599	
Total Return	3.9027	1.4595	3.5604	1.4595	2.5381	1.4595	3.1462	1.4595
Max Drawdown	0.6244	0.6083	0.5975	0.6083	0.5799	0.6083	0.6143	0.6083
Drawdown Detection Threshold	0.05		0.05		0.05		0.05	
Number of Drawdowns Over Threshold	10	10	11	10	10	10	9	10

INTL JGAM 20 YR – EAFE; Equal Weighted; Includes Transaction Costs

	INTL RCTEF		INTL REG9CTEF		INTL REG8		INTL REG 10	
	TO(20)	EAFE	TO(20)	EAFE	TO(20)	EAFE	TO(20)	EAFE
Sharpe Ratio	49%	33%	50%	33%	38%	33%	50%	33%
Information Ratio	**0.427**		**0.478**		**0.103**		**0.431**	
Realized Standard Deviation	17%	18%	17%	18%	17%	18%	16%	18%
Realized Tracking Error	**5.7%**		**5.7%**		**5.6%**		**5.5%**	
Annual Rate of Return	**8%**	**6%**	**8%**	**6%**	**6%**	**6%**	**8%**	**6%**
P/S Turnover	122%		122%		121%		122%	
Turnover	258%		258%		259%		258%	
Long Turnover	258%		258%		259%		258%	
Short Turnover	0%		0%		0%		0%	
Trade Win/Loss	0.6579		0.6169		0.6067		0.6386	
Total Return	2.2027	1.2867	2.3473	1.2867	1.4821	1.2867	2.1778	1.2867
Max Drawdown	0.6672	0.6041	0.6146	0.6041	0.6235	0.6041	0.6363	0.6041
Drawdown Detection Threshold	0.05		0.05		0.05		0.05	
Number of Drawdowns Over Threshold	7	10	8	10	7	10	9	10

INTL JGAM 20 YR – EAFE; Equal Weighted; +/- 4%; Includes Transaction Costs

	INTL RCTEF		INTL REG9CTEF		INTL REG8		INTL REG 10	
	TO(20)	EAFE	TO(20)	EAFE	TO(20)	EAFE	TO(20)	EAFE
Sharpe Ratio	49%	33%	48%	33%	35%	33%	48%	33%
Information Ratio	**0.403**		**0.423**		**0.047**		**0.386**	
Realized Standard Deviation	17%	18%	17%	18%	17%	18%	16%	18%
Realized Tracking Error	**6.1%**		**5.4%**		**5.9%**		**5.6%**	
Annual Rate of Return	**8%**	**6%**	**8%**	**6%**	**6%**	**6%**	**8%**	**6%**
P/S Turnover	122%		122%		121%		122%	
Turnover	258%		259%		258%		258%	
Long Turnover	258%		259%		258%		258%	
Short Turnover	0%		0%		0%		0%	
Trade Win/Loss	0.6242		0.621		0.6193		0.622	
Total Return	2.2214	1.2867	2.1523	1.2867	1.378	1.2867	2.0976	1.2867
Max Drawdown	0.6674	0.6041	0.6507	0.6041	0.6212	0.6041	0.6197	0.6041
Drawdown Detection Threshold	0.05		0.05		0.05		0.05	
Number of Drawdowns Over Threshold	7	10	10	10	7	10	9	10

Exhibit 7: Non-US Portfolio Attributions

INTL JGAM 14 YR – ACWI ex US; Equal Weighted

		RCTEF			REG8			REG9CTEF			REG10	
Row Labels	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**
Factor		**4.47%**	**3.75%**		**2.96%**	**3.68%**		**4.33%**	**3.61%**		**4.29%**	**3.53%**
Industry	**0.003**	**0.85%**	**0.95%**	**0.003**	**0.44%**	**1.31%**	**0.004**	**1.25%**	**1.11%**	**0.004**	**1.09%**	**1.13%**
Style	**0.720**	**3.69%**	**2.06%**	**0.463**	**3.10%**	**2.21%**	**0.581**	**3.98%**	**1.99%**	**0.691**	**4.68%**	**1.98%**
Exchange Rate Sensitivity	0.086	-0.11%	-0.06%	0.045	0.01%	-0.03%	0.064	-0.01%	-0.04%	0.058	-0.07%	-0.04%
Growth	0.131	0.36%	0.17%	0.123	-0.05%	-0.06%	0.144	0.12%	0.04%	0.138	0.15%	0.10%
Leverage	0.060	-0.13%	0.08%	0.144	-0.20%	0.25%	0.079	-0.23%	0.16%	0.058	-0.04%	0.09%
Liquidity	-0.019	-0.81%	0.18%	-0.009	-0.80%	0.15%	-0.033	-1.01%	0.20%	-0.026	-1.03%	0.21%
Medium-Term Momentum	0.287	2.30%	0.85%	-0.284	-1.20%	0.56%	-0.074	0.18%	0.31%	0.168	1.15%	0.51%
Short-Term Momentum	0.065	-1.30%	0.34%	0.000	-0.49%	0.21%	0.029	-1.29%	0.24%	0.027	-0.32%	0.18%
Size	-0.324	2.03%	1.66%	-0.349	1.76%	1.62%	-0.306	1.90%	1.55%	-0.292	1.98%	1.53%
Value	0.389	2.18%	-0.03%	0.785	3.13%	0.80%	0.687	3.48%	0.58%	0.567	3.25%	0.23%
Volatility	0.044	-1.28%	0.14%	0.008	0.12%	0.25%	-0.010	0.32%	0.42%	-0.008	-0.07%	0.56%
Market	**0.003**	**1.33%**	**-0.09%**	**0.003**	**0.63%**	**-0.06%**	**0.004**	**1.31%**	**-0.09%**	**0.004**	**1.40%**	**-0.10%**
Global Market	0.003	1.33%	-0.09%	0.003	0.63%	-0.06%	0.004	1.31%	-0.09%	0.004	1.40%	-0.10%
Stock Specific			**2.41%**			**2.46%**			**2.38%**			**2.36%**

INTL JGAM 14 YR – ACWI ex US; Equal Weighted; +/- 4%

		RCTEF 4.0			REG8 4.0			REG9CTEF 4.0			REG10 4.0	
Row Labels	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**
Factor		**5.02%**	**3.90%**		**3.29%**	**3.65%**		**4.69%**	**3.62%**		**4.23%**	**3.58%**
Industry	**0.004**	**0.87%**	**0.94%**	**0.003**	**0.11%**	**1.47%**	**0.003**	**0.85%**	**1.30%**	**0.004**	**0.51%**	**1.23%**
Style	**0.744**	**4.17%**	**2.16%**	**0.533**	**3.49%**	**2.19%**	**0.606**	**4.51%**	**1.98%**	**0.710**	**5.03%**	**2.00%**
Exchange Rate Sensitivity	0.079	-0.12%	-0.02%	0.039	0.02%	-0.02%	0.054	0.01%	-0.02%	0.053	-0.05%	-0.01%
Growth	0.157	0.51%	0.15%	0.129	0.01%	-0.05%	0.163	0.15%	0.01%	0.159	0.23%	0.09%
Leverage	0.020	-0.09%	0.04%	0.140	-0.26%	0.22%	0.012	-0.41%	0.09%	-0.010	-0.03%	0.09%
Liquidity	-0.031	-1.03%	0.21%	-0.006	-0.90%	0.11%	-0.035	-1.21%	0.19%	-0.026	-1.08%	0.19%
Medium-Term Momentum	0.302	2.44%	0.91%	-0.266	-1.28%	0.49%	-0.060	0.27%	0.24%	0.180	1.31%	0.53%
Short-Term Momentum	0.072	-1.98%	0.39%	0.003	-0.70%	0.22%	0.031	-1.32%	0.24%	0.028	-0.25%	0.18%
Size	-0.291	2.14%	1.56%	-0.289	1.71%	1.45%	-0.229	1.72%	1.28%	-0.232	1.76%	1.33%
Value	0.436	2.38%	0.01%	0.841	3.48%	0.78%	0.752	3.88%	0.59%	0.626	3.35%	0.25%
Volatility	-0.002	-0.46%	0.50%	-0.057	0.50%	0.63%	-0.081	0.92%	0.87%	-0.068	0.38%	0.88%
Market	**0.004**	**1.61%**	**-0.12%**	**0.003**	**0.96%**	**-0.07%**	**0.003**	**1.69%**	**-0.07%**	**0.004**	**6.94%**	**-0.09%**
Global Market	0.004	1.61%	-0.12%	0.003	0.96%	-0.07%	0.003	1.69%	-0.07%	0.004	6.94%	-0.09%
Stock Specific			**3.02%**			**3.06%**			**2.98%**			**2.92%**

INTL JGAM 14 YR – EAFE; Equal Weighted

		RCTEF			REG8			REG9CTEF			REG10	
Row Labels	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**
Factor		**3.01%**	**3.29%**		**1.73%**	**3.39%**		**3.01%**	**3.25%**		**3.20%**	**3.29%**
Industry	**0.002**	**0.69%**	**1.28%**	**0.001**	**-0.02%**	**1.33%**	**0.002**	**0.70%**	**1.22%**	**0.002**	**0.73%**	**1.15%**
Style	**0.738**	**3.35%**	**1.96%**	**0.420**	**3.14%**	**2.02%**	**0.604**	**4.07%**	**1.79%**	**0.658**	**4.55%**	**1.84%**
Exchange Rate Sensitivity	0.083	-0.02%	-0.02%	0.034	0.06%	-0.02%	0.050	0.08%	-0.02%	0.038	0.04%	-0.01%
Growth	0.161	0.28%	0.18%	0.126	0.02%	-0.04%	0.158	0.18%	0.04%	0.152	0.21%	0.09%
Leverage	0.082	-0.02%	0.11%	0.145	-0.11%	0.27%	0.107	-0.17%	0.20%	0.079	-0.01%	0.13%
Liquidity	0.032	-0.41%	0.14%	0.031	-0.48%	0.17%	0.013	-0.61%	0.15%	0.006	-0.57%	0.14%
Medium-Term Momentum	0.272	1.54%	0.86%	-0.254	-0.51%	0.55%	-0.042	0.69%	0.31%	0.160	1.23%	0.49%
Short-Term Momentum	0.051	0.05%	0.28%	-0.006	0.12%	0.22%	0.022	-0.18%	0.21%	0.018	0.35%	0.14%
Size	-0.309	1.73%	1.48%	-0.350	1.64%	1.53%	-0.307	1.73%	1.45%	-0.303	1.83%	1.49%
Value	0.292	1.65%	-0.10%	0.634	2.53%	0.59%	0.565	2.80%	0.41%	0.476	2.59%	0.09%
Volatility	0.073	-0.88%	0.30%	0.061	-0.04%	0.13%	0.038	0.22%	0.22%	0.032	0.07%	0.34%
Market	**0.002**	**0.91%**	**-0.05%**	**0.001**	**0.38%**	**0.02%**	**0.002**	**0.92%**	**-0.03%**	**0.002**	**1.00%**	**0.00%**
Global Market	0.002	0.91%	-0.05%	0.001	0.38%	0.02%	0.002	0.92%	-0.03%	0.002	1.00%	0.00%
Stock Specific			**2.35%**			**2.45%**			**2.35%**			**2.34%**

INTL JGAM 14 YR – EAFE; Equal Weighted; +/- 4%

		RCTEF 4.0			REG8 4.0			REG9CTEF 4.0			REG10 4.0	
Row Labels	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**	**Active Exposure**	**Active Return***	**Tracking Error**
Factor		**3.13%**	**3.35%**		**1.65%**	**3.38%**		**3.32%**	**3.27%**		**3.23%**	**3.25%**
Industry	**0.002**	**0.23%**	**1.50%**	**0.001**	**-0.45%**	**1.60%**	**0.001**	**0.14%**	**1.45%**	**0.001**	**0.15%**	**1.36%**
Style	**0.917**	**3.95%**	**1.89%**	**0.530**	**3.63%**	**2.01%**	**0.686**	**4.75%**	**1.73%**	**0.722**	**4.93%**	**1.83%**
Exchange Rate Sensitivity	0.077	-0.04%	0.01%	0.021	0.06%	-0.02%	0.042	0.09%	-0.01%	0.035	0.03%	0.02%
Growth	0.206	0.39%	0.18%	0.132	0.06%	-0.05%	0.181	0.24%	0.01%	0.177	0.27%	0.09%
Leverage	0.109	-0.20%	0.12%	0.151	-0.13%	0.25%	0.047	-0.26%	0.13%	0.016	-0.02%	0.12%
Liquidity	0.016	-0.42%	0.15%	0.034	-0.41%	0.11%	0.007	-0.70%	0.11%	0.004	-0.61%	0.14%
Medium-Term Momentum	0.281	1.63%	0.85%	-0.245	-0.62%	0.50%	-0.035	0.52%	0.19%	0.177	1.12%	0.54%
Short-Term Momentum	0.055	-0.01%	0.33%	-0.006	0.07%	0.25%	0.025	-0.17%	0.27%	0.019	0.39%	0.17%
Size	-0.256	1.72%	1.26%	-0.282	1.53%	1.32%	-0.229	1.57%	1.17%	-0.230	1.53%	1.19%
Value	0.391	2.04%	0.01%	0.746	2.80%	0.71%	0.686	3.32%	0.51%	0.570	2.87%	0.17%
Volatility	0.037	-0.28%	0.43%	-0.020	0.49%	0.36%	-0.039	0.99%	0.46%	-0.045	0.74%	0.73%
Market	**0.002**	**1.03%**	**-0.04%**	**0.001**	**0.23%**	**0.02%**	**0.001**	**1.27%**	**0.03%**	**0.001**	**1.11%**	**0.02%**
Global Market	0.002	1.03%	-0.04%	0.001	0.23%	0.02%	0.001	1.27%	0.03%	0.001	1.11%	0.02%
Stock Specific			**3.13%**			**3.19%**			**3.07%**			**3.02%**

Exhibit 8: A Brinson Attribution Analysis Verification of Non-US Model Active and Risk Stock Specific Returns

ACWI_JG_INTL vs. MSCI All Country World Ex-United States
Time Period: 1/2004 – 12/2016

		Model	MV, RCTEF	MV, REG8	MV, REG9CTEF	MV, REG10
		Active Total Return	7.33	3.78	9.77	10.54
		Active Contribution To Return	7.33	3.78	9.77	10.54
Brinson Attribution		Allocation Effect	1.25	-1.86	5.17	3.51
		Selection Effect	8.87	9.86	10.08	10.85
		Interaction Effect	-2.79	-4.22	-5.48	-3.82
		Total Effect	7.33	3.78	9.77	10.54
Risk Attribution		Risk Factors Effect	-1.36	-1.79	2.03	5.32
		Risk Stock Specific Effect	8.69	5.57	7.74	5.23
		Total Effect	7.33	3.78	9.77	10.54
		Risk Factors Effect T-Stat	-0.47	-1.30	0.01	0.92
		Risk Stock Specific Effect T-Stat	2.72	2.05	2.53	1.88
	Exchange Rate Sensitivity	Compounded Factor Impact	-0.09	-0.02	0.01	0.01
		Factor Impact T-Stat	-1.12	-0.56	-0.20	-0.09
	Growth	Compounded Factor Impact	0.77	0.23	0.66	0.81
		Factor Impact T-Stat	4.62	2.39	5.36	6.07
	Leverage	Compounded Factor Impact	0.74	0.17	0.21	0.37
		Factor Impact T-Stat	2.30	1.09	1.32	1.36
	Liquidity	Compounded Factor Impact	-0.01	-0.10	-0.08	-0.06
		Factor Impact T-Stat	0.13	-0.69	-0.56	-0.30
	Medium-Term Momentum	Compounded Factor Impact	0.50	-1.47	-1.49	-0.83
		Factor Impact T-Stat	1.23	-7.54	-4.92	-2.12
	Short-Term Momentum	Compounded Factor Impact	-0.91	-0.69	-0.98	-0.59
		Factor Impact T-Stat	-1.64	-2.24	-2.65	-1.09
	Size	Compounded Factor Impact	-0.03	-0.04	0.23	0.48
		Factor Impact T-Stat	0.26	-0.19	-0.25	0.73
	Value	Compounded Factor Impact	1.01	1.32	1.54	1.39
		Factor Impact T-Stat	4.00	6.79	5.80	5.35
	Volatility	Compounded Factor Impact	-0.45	-0.17	-0.18	-0.32
		Factor Impact T-Stat	-0.97	-0.20	-0.46	-0.81
	Market	Compounded Factor Impact	0.00	-0.05	-0.03	-0.05
		Factor Impact T-Stat	-0.15	-0.28	-0.16	-0.31
	Local	Compounded Factor Impact	0.08	-0.00	-0.00	0.01
		Factor Impact T-Stat	0.77	0.00	0.03	0.86
	Industry	Compounded Factor Impact	-0.67	-0.36	1.95	2.68
		Factor Impact T-Stat	-0.54	-0.88	1.86	2.06
	Country	Compounded Factor Impact	-1.98	-1.51	-0.80	-0.53
		Factor Impact T-Stat	-0.72	-0.99	-0.09	0.11
	Currency	Compounded Factor Impact	-0.32	0.90	0.99	1.94
		Factor Impact T-Stat	-0.50	0.14	-0.10	0.26

Table 9: CTEF Boolean Signal Attribution Analysis Summary of Axioma Attribution Result

Time Period: 1/2003 - 12/2016						
		Active	Specific	Factor	Information	Tracking
Universe	Model	Return (t)	Return (t)	Contr. (t)	Ratio	Error
XUS	RCTEF	8.15 (5.12)	5.02 (5.12)	3.13 (2.03)	1.37	6.45
R3	RCTEF	6.88 (3.43)	7.24 (9.75)	-0.36 (-0.21)	0.92	7.52
Time Period: 1/2012 - 12/2017						
		Active	Specific	Factor	Information	Tracking
Universe	Model	Return (t)	Return (t)	Contr. (t)	Ratio	Error
XUS	RCTEF	3.14 (1.44)	3.52 (4.010	-.38 (-.18)	0.64	4.87
R3	RCTEF	5.84 (1.82)	4.53 (4.82)	1.32 (0.45)	0.81	7.19

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