

A Modest Defense of Active Management

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Abstract

The purpose of this study is to document the existence of statistically significant Active Returns and positive Specific Returns (positive stock selection) in portfolios created by variable tilts linked to financial anomalies known during the 1997-2003 time period with particular emphasis on earnings forecasts. It then tests whether these variables have held up through the 2003-2018 time period. We report three results: (1) many of the reported financial anomalies published in the 1993 – 2003 time period, and particularly well post the Global Financial Crisis, 2010-2018; (2) the anomalies are larger in non-U.S. markets than in the U.S.; and (3) reasonable transactions costs do not destroy the excess returns.

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I. INTRODUCTION

This applied investment research report is written from the perspective of a quantitative researcher working in a Wall Street environment for the past 30-plus years. For the sake of simplicity, let us assume a 1986 start date, as was reported in Guerard and Markowitz (2019). We share four major insights with our stakeholders in this report. First, we report the continued statistical significance of the McKinley Capital Management Public (MCM) model of forecasted earnings acceleration, CTEF, in producing significant Active Returns and Specific Returns, stock selection, in Non-U.S. and global stock universes. Second, CTEF and robust-regression models of stock selection models produce optimized portfolios that deliver highly significant Active and Specific Returns in Non-U.S. stocks. Have markets and stock selection models changed since Guerard and Mark (2003) and Guerard et al. (2013) published their studies? No, CTEF and robust regression models still dominate most other models, including the 36 models tested in Guerard et al. (2018), including the Post-Global Financial Crisis period. Third, we have tested many commercially available risk models and we report, over the past 7-9 years, that there are several risk models capable of producing highly statistically significant Active and Specific Returns. However, we at MCM use the Axioma Statistical Risk Model because of its performance in MCM research competitions (the "Horse Race)" and its integration with the ITG cost curves data. Fourth, Guerard et al. (2018) also show that updated models pass the Level III Data Mining Corrections test of Markowitz and Xu (1994) for statistical significance. Models will never be perfect, but their portfolios can be statistically significant.

Financial anomalies and regularities in returns have been studied for over 80 years in the U.S. If these patterns are both persistent and observable, investors should incorporate this information into their decision-making, financial plans and portfolio construction; even despite the noise of the day, financial media and distractions associated with investing. The importance of taking account of return regularities in portfolios and plans arises because these patterns may reflect premia serving as a reward for risk-taking or because they represent classical measures of "alpha." Of extreme importance to individual and institutional investors alike is whether they are on the "other side of the trade" and whether they are risk-sharing in markets or giving up alpha to smarter investors.

Specifically, we test a set of U.S. and Non-U.S. variables over the past 15 years, despite rumors to the contrary, and find that many of these fundamental, earnings forecasts, revisions, and breadth variables have maintained their importance for returns. Moreover, earnings forecasting model excess returns are greater in Non-U.S. and Global markets than in the U.S. markets in their post-publication time period, including booms, recessions, and highly volatile market conditions. Overall, we find that non-U.S. and Emerging Markets portfolios, built on quantitative-based variables and models, have produced statistically significant Active Returns and positive Specific Returns (positive stock selection) for 5-years, 10-years, and since-inception. The underlying Quant Models, built on anomalies known at the time, have outperformed indexes in over 70-80% of the years.

The Efficient Markets Hypothesis (EMH) dates back to Roberts (1959) and his three forms of efficiency. The EMH simply put, held that stock prices reflected information. The weak form of the EMH held that all past stock prices and volume information was incorporated into share prices. Hence, technical analysis would not produce statistically significant excess returns. The semi-strong form held that all public information, such as earnings, stock splits, earnings forecast, merger announcements, and Federal Reserve announcements were incorporated into share prices, Fama (1970, 1976). Hence, fundamental analysis would not produce statistically significant excess returns. The third form, the strong form, held that all information was incorporated into share prices. Hence, non-public information such as fund performance and insider trading would not produce statistically significant excess returns above transactions costs, and data mining corrections adjustments in U.S. and non-U.S. stocks during the 2003-2018 time period, using models published by the authors in 1993 and 1997.

Fama (1976) assumes all events happen at discrete time, t - 1, t, t + 1. He defines =

 Φ_{t-1} = set of information available at the time t-1 to determine stock prices at t-1.

 Φ_{t-1}^m = set of information the market uses to determine stock prices at time t-1



 $p_j, t-1 =$ price of stock j at time t-1

j = 1, 2, ..., n where n is the number of stocks in the market

$$f_m(p_1, t + \tau, ..., p_n, t + \tau | \Phi^m = \text{joint profitability density } t - 1$$
 function for stock prices

at time $t + \tau$ assessed by the market at time t - 1, based on information Φ_{t-1}^m .

An efficient capital market is written as:

$$\Phi_{t-1}^m = \Phi_{t-1} \tag{1}$$

That is the market uses all available information.

A one period price relative return is written:

$$\tilde{R}_{jt} = \frac{\tilde{p}_{jt} - p_{j,t-1}}{p_{j,t-1}}$$
(2)

Stock return is given by:

$$E_m(\tilde{R}_{jt} \mid \Phi_{t-1}) = \frac{\widetilde{p}_{jt} \mid \Phi_{t-1}^m - p_{jt}}{p_{j't-1}}$$
(3)

The market sets p_j , $_{t-1}$ and most empirical evidence pre-2000 supported the weak form of the EMH.¹

A second market efficiency test is concerned with the speed of price adjustments to publicly available information. Stock returns conform to the market model. The semi-strong test is used in conjunction with announcements of stock splits, earnings, new share issues, mergers, and earnings forecasting. In table tests, we test if the table joint distribution of different stock prices is multivariate normal. That is, we use the CAPM relationship of risk and return to establish the tests of the value of public information.

$$E(\tilde{R}_{jt} \mid \Phi_{t-1}, R_{mt}) = \alpha_j + \beta_j R_{mt}$$
(4)

$$\beta = \frac{\cos\left(\tilde{R}_{j}, \tilde{R}_{m}\right)}{\sigma^{2} \tilde{R}_{mt}}$$
(5)

$$\alpha_{j} = E(\tilde{R}_{jt} \mid \Phi_{t-1}) - \beta_{j} E(R_{mt} \mid \Phi_{t-1})$$
(6)

$$\tilde{R}_{jt} = \alpha_j + \beta_j \,\tilde{R}_{mt} + \,\tilde{\varepsilon}_{jt} \tag{7}$$

¹ See Lo, Mamaysky, and Wang (2000) for an outstanding modern test of technical analysis.

(8)

II. WHAT WE KNEW IN 1991: TESTS OF FUNDAMENTAL DATA

What did we know in 1991? What did we know in 2003? What did you know in August 2005? Students had been taught since Graham and Dodd (1934), Williams (1938), Graham, Dodd, and Cottle (1962), Loeb (1971), Graham (1973), Latane, Tuttle, and Jones (1975), and Dremen (1979) that fundamental data, earnings, cash flow, book value, net current asset value, and sales, drove stock returns. The books supported the "low price-earnings (P/E)" multiple. Stocks with low P/Es outperformed high P/Es. Basu (1977) reported recent support for the low P/E strategy. The fundamental data was complemented with small size, institutional holdings, earnings forecasts, revisions, recommendations and breadth, earnings surprises, insider trading, dividend yield, and momentum variables, being identified in Dimson (1988), Jacobs and Levy (1988).² These variables had been statistically tested, after removing market effects, and were reported as producing excess returns (adjusting for risk) and they declared anomalies. Chan et al. (1991), Bloch, et al. (1993), Fama and French (1992), Ziemba and Schwartz (1992) and Haugen and Baker (1996) discussed many of the earlier reported non-U.S. anomalies and /or compared U.S. and non-U.S. anomalies.

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. For example, Bloch et al. (1993) used relative ratios as well as current ratio values in analyzing eight factors to understand the relative explanatory power of each in an equation to estimate the determinants of total stock returns, TR. They refer to this model as REG8.

$$TR = w_0 + w_1EP + w_2BP + w_3CP + w_4SP + w_5REP + w_6RBP + w_7RCP + w_8RSP + e_t$$
(9)

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

² See Levy (1999) for a most tabular list of well-known financial anomalies.



BP	=	[book value per share]/[price per share] = book-price ratio;
СР	=	[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]; and
RSP =		[current SP ratio]/[average SP ratio over the past five years];

Financial models are plagued by both outliers, influential observations that may distort regression lines and hypothesis testing, and multicollinearity, high correlation among independent variables. Both issues were addressed in Bloch et al. (1993).

III. WHAT WE KNEW IN 1997: TESTS OF FUNDAMENTAL DATA AND EARNINGS EXPECTATIONS

Bruce and Epstein (1994)³ provided a summary of key studies of the effectiveness of corporate earnings forecasting variables. Further, Brown (2000) contained over 500 abstracts of studies using Institutional Broker Estimation Services (I/B/E/S) data.⁴ By 1997, it was known that Consensus Temporary Earnings Forecast (CTEF), a composite model of I/B/E/S consensus-based earnings yield forecasts, earnings revisions, and earnings breadth (the agreement among analysts' revisions) produced highly statistically significant correlates of stock returns. Furthermore Guerard, Stone, and Gultekin (1997)

³ The Bruce and Epstein and Brown works contain much of the rich history of earnings forecasting and resulting excess returns. Bruce and Epstein included workers the work of researchers such as Elton, Gruber, and Gultekin, who developed I/B/E/S database and published the initial research (1981 and 1984). Hawkins, Chamberlain, and Daniel (1984), the heads of IBES as it was then known, developed tests for analyst revisions. Guerard and Stone (1992), which tested time series model forecasts versus analysts' forecasts. The Elton <u>et al. (1981)</u> paper is one most influential analyses in earnings forecasting and security analysis. 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, Markowitz, and Xu (2015) reported that the 1990s earnings forecasting anomalies continued to statistically significantly enhance portfolio returns.

⁴ Analysts' forecasts of earnings per share (eps), eps revision, and the 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.



estimated a nine-factor model, REG9, composed of REG8 plus CTEF, was highly (statistically) significantly correlated with subsequent stock returns.

$$TR_{t+1} = a_0 + a_1 EP_t + a_2 BP_t + a_3 CP_t + a_4 SP_t + a_5 REP_t + a_6 RBP_t + a_7 RCP_t + a_8 RSP_t + a_9 CTEF_t + e_t,$$
(10)

where:

EP	=	[earnings per share]/[price per share] = earnings-price ratio;
BP	=	[book value per share]/[price per share] = book-price ratio;
СР	=	[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	= c	consensus earnings-per-share I/B/E/S forecast, revisions and breadth;
е	=	randomly distributed error term.

In 2005-2006, MCM launched a major research effort to "pop the hood" on its investment strategies and test whether its factors of revisions and risk-adjusted relative return (price momentum) were statistically significant. We developed the McKinley Quant (MQ) strategy of combining revisions and the risk-adjusted relative returns models into a single proprietary score, the MQ. Higher scoring stocks were preferred, and the semi-final nominations list (the SFL) was composed of stocks in the top three-deciles (scoring 70-99). Elton, Gruber, and Gultekin (1981) demonstrated the effectiveness of an upper three-decile strategy. In 2011, MCM decided to have two models: its Public Model of forecasted earnings acceleration, its CTEF model, as published by the author in Guerard, Stone, Gultekin (1997), and its proprietary model of forecasted earnings acceleration, E'.

and



IV. WHAT WE KNEW IN 2012: TESTS OF FUNDAMENTAL DATA AND EARNINGS EXPECTATIONS

Financial economists have empirically examined the determinants of stocks returns since Nerlove (1968). 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, had been studied since Bachelier in 1900, reprinted in Cootner (1964). However, influential recent research such as that of Conrad and Kaul (1989), Jegadeesh and Titman (1993), Conrad and Kaul (1991, 1993, 1998), and Lo et al. (2000) formalizes and extends the technical analysis and price momentum literature.⁵ Expanding on the work of Fama and French (1998) and Guerard and Mark (2003), Guerard et al. (2012) create a ten-factor stock selection model for the U.S. expected returns that includes price momentum – the USER model.⁶ Guerard et al. (2013) and Guerard and Mark (2018) apply a 10-factor model to global stocks, referring to the model as GLER (Global Equity Return), or REG10 (See equation 11). USER and GLER models are Public Models with (many) similar exposures to MQ in U.S. and Non-U.S. and Global stocks, respectively.

$$TR_{t+1} = a_0 + a_1 EP_t + a_2 BP_t + a_3 CP_t + a_4 SP_t + a_5 REP_t + a_6 RBP_t + a_7 RCP_t + a_8 RSP_t + a_9 CTEF_t + a_{10} PM_t + e_t, \qquad (11)$$

where:

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

⁵ Most importantly for our analysis, Conrad and Kaul (1998) report 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. Jagadeesh and Titman (1993) 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. Thus, illustrating that medium-term momentum is an important, and persistent, risk premium. In the very long-run (24 and 36-months) Conrad and Kaul (1998) show that momentum returns become very negative. Lo et al. (2000) find over the 1962 -1996 time period that technical patterns produced incremental returns, particularly for NASDAQ stocks – demonstrating price momentum and technical analysis variables enhanced portfolio returns over the long-run.

 $^{^{6}}$ Brush (2001) tested a PM121 price momentum variable, defined as P(t-1)/P(t-12) among a set of 7-12 price momentum models.



СР	=	[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	= c	consensus earnings-per-share I/B/E/S forecast, revisions and breadth;
PM	=	price momentum; and
е	=	randomly distributed error term.

The ten-factor model was developed and tested in U.S. markets in Guerard, Xu, and Gultekin (2012) and Guerard, Markowitz, and Xu (2014), and in global markets in Guerard, Rachev, and Shao (3013) and Guerard, Markowitz, and Xu (2015). Furthermore, Deng and Min (2013) reported that the GLER model produces highly statistically significant active returns and better stock selections than the USER model over the corresponding period.⁷ In addition, the earnings forecasting model, CTEF, and the GLER model continued to produce higher statistically significant Active Returns and Specific Returns (stock selection) during the 1996 -2016 time period in Non-U.S. than U.S. markets, see Guerard, Markowitz, and Xu (2015), Guerard, Markowitz, Xu, and Wang (2018), and Guerard and Mark (2018).⁸

V. MARKOWITZ: CONSTRUCTING MEAN-VARIANCE EFFICIENT FRONTIERS

The Markowitz (1952 and 1959) portfolio selection and construction approach is centered upon 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, $E(R_p)$, is calculated by taking the sum of the security

⁷ 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.

⁸ Guerard, Markowitz, and Xu (2015) studied the 1999 -2011 time period and Guerard, Markowitz, Xu and Wang (2018) studied the 2003 -May 2015 time period.

weights multiplied by their respective expected returns. The portfolio standard deviation is the sum of the weighted covariances.

$$E(R_p) = \sum_{i=1}^{N} x_i E(R_i) = \sum_{i=1}^{N} x_i \mu_i$$
(12)

$$\sigma_p^2 = \sum_{i=1}^N \sum_{j=1}^N x_i x_j c_{ij}$$
(13)

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

The efficient frontier can be traced out by

$$minimize_{\{x_i \ge 0, x_i \le \overline{u}\}} \quad x^T C x - \lambda \mu^T x \tag{14}$$

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

Risk is estimated with an k-factor index or 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 as:

$$R_j = \sum_{k=1}^K \beta_{jk} \widetilde{f}_k + \widetilde{e}_j.$$
(15)

The nonfactor, or asset-specific, return on security j, \tilde{e}_j , is the residual risk of the security after removing the estimated impacts of the *K* factors.⁹ The term f_k is the realization or rate of return associated with factor k. The factor model is used to decompose risk into systematic risk and unsystematic, or residual, risk.

$$C = \beta C_{f,f} \beta' + \Sigma. \tag{16}$$

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

⁹ The estimation of factors, or betas, can be accomplished using firm fundamental data, as in the Rosenberg (1974), Rosenberg and Marathe (1975, 1976), Rosenberg and Marathe (1979), and Menchero et al. (2010), or principal component analysis of historical stock returns, as in Blin, Bender, and Guerard (1997) and Saxena and Stubbs (2012). The reader is referred to complete and excellent surveys of multi-factor models found in Rudd and Clasing (1982), Grinold and Kahn (1999), Connor and Korajczyk (2010), and Connor, Goldberg, and Korajczyk (2010).



minimize
$$(x - x_b)^T C(x - x_b) - \lambda \mu^T (x - x_b)$$
 (17)

where x_b is the weight vector of the benchmark. One can enhance the tracking by adding equal active weighing constraints (EAW):

$$|x_j - (x_b)_j| \le y, \quad \text{for all } j \tag{18}$$

The MVTaR with constraints in Eq.(18) will be referred to as EAWTaR.

VI. COMMERCIALLY-AVAILABLE RISK MODELS

The authors have great respect for many practitioners and modelers of risk. Andrew Rudd and Dan Stefek, John Blin, Robert Stubbs and Anureet Saxena, S.T. (Zari) Rachev, and Jose Menchero have offered great insights of their models to the authors.¹⁰ Bloch, Guerard, Markowitz, Todd and Xu (1993) reported hundreds of U.S. and Japanese quantitative models and composite strategies. The strategies were tested on the basis of a full-covariance risk model and the data mining corrections factor, discussed in the Bloch <u>et al.</u> (1993) discussion of the Daiwa Global Portfolio Research Department (DPOS) system.¹¹ In 1997-1998, Blin, Bender, and Guerard (1997 and 1998) intensively studied long-only and long-short portfolio construction tests in the U.S. and Japan, using the Advanced Portfolio Technologies (APT) model. The Blin and Bender APT model was constructed based on 20 statistical orthogonal factors derived from a Principle Components Analysis (PCA) application. The Blin and Bender statistically-derived risk model can be distinguished from the premier fundamentally-based model, the BARRA US Equity Model, often

¹⁰ The authors have published with Blin, Saxena, Rachev, and Menchero.

¹¹ Bloch et al. (1993) reported Levels II and III of the three levels of testing reported in Guerard, Markowitz, and Xu (2015). The overwhelming number of variables and composite strategies would have passed Level I, but the creators of the DPOS system had no interest in testing Levels I, II, and III; but rather Levels II and III, the harder levels to pass.



denoted USE1, developed by Barr Rosenberg and others in 1973-1975.¹² Within the USE1 model, raw data are 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. A final transformation occurs when the normalized descriptor is scaled such that its value is one standard deviation above the S&P 500 mean. Every month the monthly stock returns in the quarter are regressed as a function of the normalized descriptors. The monthly residual risk factors were 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.¹³ The domestic BARRA E3 (USE3, or sometimes denoted US-E3) model has 13 sources of factor, or systematic, exposures. The sources of extramarket 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. BARRA is a now proprietary model; that is, the composite model weights are not disclosed.

In 2005-2006, when MCM popped the hood on its models, the choices commercially available risk models were the Blin and Bender model and the Barra model. MCM chose the Blin and Bender APT based on the research documented in Blin, Bender, and Guerard (1997). The original MQ analysis used the APT risk models, see the MCM Management working papers of 2006.¹⁴ About 2010, MCM asked itself if the APT risk model was the "best risk" model. The

¹² The BARRA USE1 Model predicted risk had 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). The most complete discussion of the BARRA models is found in Rosenberg and Marathe (1979) and Rudd and Clasing (1982). The latter is an excellent reference for how the BARRA equity model was constructed and how it sought to revolutionize portfolio management.

¹³ See Rudd and Clasing (1982), p. 115, for the USE1 descriptors.

¹⁴ The real-time portfolio implementation of the MCM APT models is reported in Guerard, Gillam, Markowitz, Xu, and Wang (2015), presented at the 2016 Wharton – Jacobs & Levy Forum (May 2016) and forthcoming in W.T. Ziemba, <u>Handbook of Portfolio Construction and Management</u>. The APT portfolios produced highly statistically



research interactions of Guerard and APT had given MCM a substantial commercial discount, but MCM was concerned with having an investment system produce the highest Geometric Means, Information Ratios, and Sharpe Ratios. Thus, in 2010, MCM began its first Horse Race in which the U.S. Public models, USER, was supplied to BARRA, APT, ClariFi, and FinAnalytica. APT prevailed in the USER Horse Race as documented in Guerard, Xu, and Gultekin (2012), although BARRA and FinAnalytics produced statistically significant Active and Specific Returns. Axioma joined the Horse Race in 2012 for the global set of portfolio risk models. The initial risk model Horse Race was tested during the 1998 – 2009 time period. The APT and FinAnalytica risk models performed very well, Guerard, Rachev, and Shao (2013). Miller, Xu, and Guerard (2014) extended the BARRA test in the U.S. during the 1980 – 2009 time period and again reported statistically significant Active and Asset Selection (stock selection in the BARRA system). Another commercially-available risk model is the Axioma Risk Model. The Axioma Robust Risk Model¹⁵ 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 statistical techniques, such as principal component analysis (PCA), to estimate factors. 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) to produce beta estimates with constant variance. With ordinary least squares beta estimations, one finds that large assets exhibit lower volatility than smaller assets. Axioma uses robust regressions, using the Huber M Estimator, address the issue and problem of outliers.

significant Active Returns and Specific Returns during the 2010-2015 time period, using a lambda of 200, including transactions costs!

¹⁵ <u>Axioma Robust Risk Model Handbook</u>, January 2010.



Axioma has pioneered the Alpha Alignment Factor, AAF, for effective portfolio construction. AAF recognizes the mismatch of expected returns variables and component variables in risk factors. The potential expected returns and variance mismatches can create misalignment problems and lead to the under-estimation of realized tracking errors, particularly during the 2008 Financial Crisis. Constraints may play an important role in determining the composition of the optimal 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:

$$C_{new} = C + \sigma_{\underline{\alpha}}^2 \underline{\alpha} \cdot \underline{\alpha'} + \sigma_{\underline{\gamma}}^2 \underline{\gamma} \cdot \underline{\gamma'}, \qquad (20)$$

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 γ .

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 Stubs (2012) applied the AAF to a Core McKinley public model (USER) and reported that the EP and BP ratios had misalignment coefficients of over 68%, respectively. In the process of doing so, AAF approach, creates a missing systematic risk factor not only improves the accuracy of risk prediction, but shifts out the efficient frontier. Saxena and Stubbs reported that the AAF process pushed out the traditional risk model-estimated efficient frontier. 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.¹⁶

Past performance is not indicative of future returns.



VII. THE EXISTENCE AND PERSISTENCE OF FINANCIAL ANOMALIES: 2003 – 2018

In this section, we discuss several recent anomalies tests and report on global financial anomalies. We find that many of the previously identified financial anomalies have continued to produce statistically significant Active and Specific Returns in the post-publication periods, 1993 – 2014 and 2003 – 2018.

Guerard et al. (2015) reported three levels of testing investment strategies. 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 second level of investment testing is to estimate, with transactions costs, the Markowitz efficient frontier the targeted tracking error in Axioma or the lambda in APT. 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. Guerard, Markowitz, and Xu (2014) presented a recent U.S. data mining corrections tests, 2000-2012, and the results substantiated the U.S. stock results reported in Bloch et al. (1993).

In this section, we revisit the Guerard, Rachev, and Shao (2013) universe results for the top 7500 largest market-capitalized global stocks with at least two analysts' forecasts, January 2003 – December 2014. Our simulation conditions assume 8 percent monthly turnover, 35 basis point threshold positions, an upper bound in Mean-Variance optimization of 4 percent on security weights, and ITG transactions costs¹⁷. We use two Mean-Variance Tracking Error at Risk, MVTaR, where 20 orthogonal (Principal Components

¹⁶Saxena and Stubbs (2012) define the factor alignment problem (FAP), which arises as a result of the complex interactions between the factors used for forecasting expected returns, risks and constraints.¹⁶ 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. Expected-return modelers are interested in the first moment of the equity return process, while risk modelers focus on the second moments. 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.

Past performance is not indicative of future returns.

¹⁷ ITG, the Investment Technology Group, estimates our transactions costs to be about 60 basis points, each-way, for 2011-2015.



Analysis) betas are estimated. Our portfolio looks almost exactly like the market index benchmark, the MSCI All Country World ex US index, on 20 dimensions. MVTaR maximizes returns while minimizing the underperformance of an index portfolio return. An increase in lambda, the measurement of risk tolerance, serves to produce portfolios with higher geometric means (GM), Sharpe ratios (ShR), and information ratios (IRs). If one seeks to maximize the geometric mean of a portfolio, consistent with Latane (1959) and Markowitz (1959), then one should employ a lambda of at least 200.¹⁸ The efficient frontiers of the MVTaR portfolios report substantial excess returns for any given level of risk. We ran a large (seemingly infinite) set of portfolio efficient frontiers, varying the ratio of systematic risk to total risk,¹⁹ and find that the tracking error at risk formulation is an optimal solution for the GLER data, at least for this specific time frame. However, we remind readers that there is an infinite set of portfolios that lie on or near the efficient frontier.

Modern robust statistics minimize a scale measure of residuals insensitive to large residuals, such as the median of the absolute residuals, see Maronna, Martin, and Yohai (2006), and Maronna, Martin, Yohai, and Salibian-Barrera (2019). The least median squares (LMS) estimator was introduced by Hampel (1975) and Rousseeuw (1984). When we use a very large efficiency measure such as 99 percent, large outliers have virtually no influence on the regression estimates. The larger the efficiency, the larger the bias under contamination, and there can be a trade-off between normal efficiency and contamination by outlier bias. The SAS ROBUSTREG procedure in SAS uses an 85 percent efficiency default level as a result of Maronna, Douglas, and Yohai (2006). We use 99 percent because of research conversations with Doug Martin, see Guerard (2017), and the resulting higher portfolio simulation Sharpe Ratios.

We show that the financial anomalies of EP, BP, CP, SP, CTEF, and PM are analyzed within REG10 with the Tukey and Yohai presented in Table 1 with the MVTaR optimizations, outperforms the

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¹⁸ The authors believe that the use of lambdas that are less than the levels that maximize the geometric mean or the Sharpe ratio is due to investors' preferences. The authors prefer to maximize the GM and ShR criteria, even if the tracking errors are larger than those of enhanced-index strategies.

¹⁹ Readers may request information regarding the set of additional trade-off curves and analyses from the corresponding author, John Guerard.



MSCI All Country World ex Us benchmark for the 2003 – 2014 time period.²⁰ There is a risk-return tradeoff. Consistent with Bloch et al. (1993), Guerard, Rachev, and Shao (2013), and Guerard, Markowitz, and Xu (2015), as lambda, a measure of risk tolerance, rises then portfolio returns rise and standard deviations rise. The Information Ratio, the ratio of portfolio Active (Excess) Return relative to the portfolio tracking error, TE, is maximized with a realized tracking error in excess of 8 percent, producing an Information Ratio (IR) of 1.53 and statistically significant Active and Specific Returns (t = 5.28 and 4.66, respectively). The MVTaR Tukey and Yohai OIF99% regressions maximize the Active and Specific Returns (1250 and 600 basis points). That is, we estimate the REG10 model using the Tukey and Yohai Optimal Influence Function (OIF99) with 99% efficiency levels. The OIF99 Tukey and Yohai regressions produce an interesting set of optimization results. First, the Sharpe Ratio rises with an increased lambda, a measure of risk tolerance, and realized tracking errors. Second, the Information Ratio rises with increased lambda and realized tracking errors with the MVTaR optimization techniques. If one seeks to maximize the Geometric Mean and Sharpe Ratio, then a realized 8 percent TE is warranted using lambdas of 200 or 500. The optimized portfolios outperform in 70% and 77% of the years, respectively. Financial anomalies, as published in 2003 and 2012-3 continue to outperform.

One can use the Axioma Fundamental Risk Model, version 4, to perform access portfolio selection and construction. The Axioma Robust Risk Modelⁱ is a multiple-factor risk model, in the tradition of the Barra model and equation (7). Axioma offers both US and World Fundamental and Statistical Risk Models.²¹ The Axioma Risk Models use several statistical techniques to efficiently estimate factors. The

²⁰ Guerard, Markowitz, Xu, and Wang (2018) also documented the persistence of common stock issues and buybacks that were tested in Fu and Huang (2016) and Chu, Hirshleifer, and Ma (2017).

Past performance is not indicative of future returns.

²¹ McKinley Capital Management re-examined the FactSet-based GLER database and test the usefulness of the alpha alignment factor in two applications. First, we create GLER portfolios using the Axioma world-wide statistically-based risk model and the Axioma world-wide fundamentally-based risk model, discussed in the attribution analysis.²¹ Guerard (2013) created efficient frontiers using both of the Axioma risk models, and found that the statistically-based Axioma risk model, STAT, produced higher geometric means, Sharpe ratios, and information ratios than the Axioma fundamental risk model, FUND. We report a larger set of tracking error optimizations with the same result; higher 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. We find that statistically-based risk models using principal components, such



18

ordinary least squares residuals (OLS) are not homoscedastic; 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).

The Axioma Risk Models use 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. In 2011, MCM Management, LLC (MCM) initiated a "Horse Race" testing procedure to test if all optimizers were created equal. They are not. In 2011, APT and Axioma were the winners among several (4–5) optimization systems using the MCM U.S. "Public Models" CTEF and REG8, REG9, and REG10 Models, and combinations therein demand USER in the US and GLER in global markets.

Let us update the 2012 MCM Horse Race analyses. In the MSCI All Country World ex-US universe, during the 12/2002 – 11/2018 time period, the ranked EP and CTEF variables produced highly statistically significant Active Returns and Specific Returns, see Table 2. The role of historical and forecasted earnings in the Non-U.S. universe is well documented, as in Guerard, Markowitz, and Xu (2015). The EP and CTEF portfolio Geometric Means, Sharpe Ratios, and IRs are followed by REG8, REG9, and REG10, see Table 2. The Low P/E and CTEF variables produced statistically significant portfolio Active Total returns and Stock Specific Returns in the Non-U.S. universe. The EP, CTEF, REG8, REG9, and REG10 Mean-Variance portfolios produce statistically significant portfolio Active and Specific Returns.

as Sungard APT and Axioma, produce more efficient trade-off curves than fundamentally-based risk model using our variables.



Total The EP, CTEF, REG8, REG9, and REG10 Mean-Variance portfolios produce statistically significant

portfolio Active Returns and significant Stock Specific Returns for the 1/2003 -11/2018 time period in

foreign markets.²² Table 2: Mean-Variance Anomalies Portfolios Robust Regression Models with Tukey OIF99% Time Period: 12/2002 -11/2018

		Risk					Axioma			
	Risk	Stock		Risk		R	isk Factor Return	5		
	Stock	Specific	Risk	Factors	Risk					
	Specific	Effect	Factors	Effect	Total	Earnings	Medium-Term			
Portfolios	Effect	T-Stat	Effect	T-Stat	Effect	Yield	Momentum	Size	Value	Volatility
Universe: MSCI ex US										
REG8_TE4	5.48	2.73	1.31	1.72	6.79	0.12	-0.91	0.95	1.21	-0.70
REG8_TE6	6.94	2.76	0.78	1.71	7.72	0.07	-1.18	1.31	1.82	-1.86
REG8_TE8	7.96	2.75	0.29	1.73	8.26	-0.04	-0.92	1.40	2.25	-2.77
REG9_TE4	5.38	2.61	2.35	2.80	7.73	0.37	-0.20	0.84	1.24	-0.49
REG9_TE6	5.49	2.13	2.60	2.93	8.09	0.36	-0.21	1.20	1.89	-1.62
REG9_TE8	5.52	1.87	2.57	2.80	8.09	0.31	-0.01	1.31	2.39	-2.36
REG10_TE4	3.07	1.65	3.93	3.62	7.00	0.46	0.56	0.74	1.12	-0.31
REG10_TE6	3.03	1.49	5.04	3.66	8.08	0.54	0.90	1.04	1.65	-1.31
REG10_TE8	2.95	1.37	5.72	3.47	8.67	0.57	1.17	1.03	1.89	-1.64
EP_TE4	7.32	3.70	1.75	2.34	9.07	0.58	0.91	0.08	-0.44	-0.22
EP_TE6	8.78	3.68	1.03	2.04	9.81	0.68	0.88	0.07	-0.23	-0.37
EP_TE8	9.78	3.71	1.31	2.22	11.09	0.64	0.72	0.12	-0.05	-0.49
CTEF_TE4	5.90	3.35	4.02	3.55	9.92	0.76	0.67	-0.13	1.78	0.30
CTEF_TE6	6.56	3.33	4.79	3.29	11.34	0.92	0.62	-0.03	2.55	0.44
CTEF_TE8	6.82	3.26	5.35	3.07	12.17	1.00	0.55	-0.10	3.07	0.61
Universe: MSCI EM										
REG8_TE4	3.99	2.38	1.79	2.11	5.78	0.25	-0.85	0.61	1.61	0.18
REG8_TE6	3.30	1.64	2.32	2.17	5.63	0.13	-0.99	1.00	2.46	-0.37
REG8_TE8	3.37	1.36	2.59	2.27	5.96	0.00	-0.78	1.20	2.84	-0.74
REG9 TE4	3.45	2.20	3.28	3.60	6.73	0.43	-0.19	0.49	1.69	0.27
REG9 TE6	2.62	1.54	4.37	3.49	6.99	0.41	-0.09	0.82	2.57	-0.23
REG9_TE8	3.40	1.73	5.09	3.31	8.50	0.38	0.25	1.04	3.21	-0.62
REG10_TE4	2.25	1.58	4.06	4.24	6.31	0.44	0.53	0.43	1.68	0.21
REG10_TE6	1.33	1.07	5.63	4.17	6.96	0.41	0.93	0.73	2.60	-0.30
REG10_TE8	0.30	0.59	6.34	3.68	6.64	0.39	1.32	0.87	3.16	-0.61
EP_TE4	2.06	1.28	2.66	3.21	4.72	0.52	-0.71	0.61	1.40	0.36
EP_TE6	3.85	1.98	2.96	3.06	6.81	0.63	-0.71	0.81	1.92	0.02
EP_TE8	3.20	2.16	3.84	4.42	7.04	0.63	1.51	0.30	0.47	-0.06
CTEF_TE4	3.67	2.13	4.67	4.02	8.34	0.90	2.13	0.49	0.73	-0.70
CTEF_TE6	3.67	2.13	4.67	4.02	8.34	0.90	2.13	0.49	0.73	-0.70
CTEF_TE8	3.54	2.18	5.76	3.64	9.30	0.87	2.69	0.62	0.93	-1.37

BOLD DENOTES STATISTICALLY SIGNIFICANT ACTIVE AND RISK STOCK SPECIFIC EFFECT AT THE 10% LEVEL

where

Risk Stock Specific Effect = Portfolio Stock Selection Contribution Risk Factor Effect = Portfolio Factor Return Contributions

Risk factor Enect = Fortiono factor Return contributions

²² 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. ²² The R3 and XUS model correctly rank-order stocks; that is, to buy R3 stocks exceeding 85, hold them in equally-

We have shown how forecasted earnings acceleration produces highly statistically significant stock selection in Non-U.S. stocks, 2003 -2018. CTEF, REG8, REG9, and REG10 models optimized portfolios produce higher Active and Specific Returns in Non-U.S. stocks than U.S. stocks, see Guerard, Markowitz, and Xu (2015), Guerard, Markowitz, Xu, and Wang (2018).²³

IX: REAL-TIME RESULTS

In 1993, Bloch et al. (1993) and Guerard, Takano, and Yamane (1993) reported real-time results in footnotes in the peer-refereed articles. Guerard and Markowitz believed strongly that quantitative modeling, without statistically significant real-time performance, did not enhance client wealth. Guerard and Chettiappan (2017) reported how a MCM Management Emerging Growth (EM) strategy had been formulated in 2006, funded in 2011, and had been a top-decile performing strategy in real-time. An updated performance attribution of the EM portfolio is reported in Table 3. The EM portfolio has produced over 450 basis points, annualized, of Active Returns (statistically significant, since-inception).

weighted portfolios until their monthly CTEF score falls below 70, produced an annualized Active Return of 6.88%, composed of highly statistically significant stock selection (Specific Returns), see Table 30.11. A similar test to buy XUS stocks exceeding 85, hold them in equally-weighted portfolios until their monthly CTEF score falls below 70, produced annualized Active Returns of 8.15%, see Table 30.11. 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. The world is changing; but 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.

Past performance is not indicative of future returns.

²³ See the Factor IC Performance Charts for Non-US and EM universes for five-year and 10-year variables, see Table 8, as of December 2018. CTEF and MQ were well-chosen variables in 2006 and during the post-GFC time period.



Table 3: EM Attribution vs. MSCI Emerging Markets Index FACTOR ATTRIBUTION: FACTOR CONTRIBUTION McKinley Capital Emerging Markets Growth Representative Portfolio

Period: 03-31-2011 through 12-31-2018 Currency: United States Dollar

		Avg		Realized	Information	
Source of Return*	Contribution	Exposure	Hit Rate	Risk	Ratio	T-Stat
Portfolio	5.09%			16.72%		
Benchmark (MSCI Emerging Markets Index)	0.57%			16.87%		
Active	4.51%	>		6.04%	0.75	2.08
Specific Return	0.37%	>		4.34%	0.09	0.24
Factor Contribution	4.14%			3.75%	1.10	3.07
Style	2.61%			2.32%	1.13	3.13
Dividend Yield	-0.17%	-0.15750	40.86%	0.14%	-1.19	-3.31
Earnings Yield	-0.04%	-0.13931	44.09%	0.19%	-0.19	-0.52
Exchange Rate Sensitivity	0.05%	0.05202	58.06%	0.07%	0.77	2.15
Growth	-0.16%	0.32104	46.24%	0.27%	-0.59	-1.65
Leverage	0.05%	-0.11242	53.76%	0.10%	0.55	1.52
Liquidity	-0.09%	0.05595	46.24%	0.11%	-0.84	-2.33
Market Sensitivity	-0.10%	-0.12500	56.99%	0.56%	-0.19	-0.52
Medium-Term Momentum	3.35%	0.67175	74.19%	1.71%	1.96	5.46
Profitability	0.75%	0.32778	77.42%	0.27%	2.83	7.87
Size	0.40%	-0.10160	59.14%	0.40%	1.00	2.79
Value	-0.55%	-0.38581	46.24%	0.59%	-0.94	-2.62
Volatility	-0.89%	0.19471	36.56%	0.62%	-1.44	-4.00
Market	-0.34%	-3.96%		0.46%	-0.75	-2.09
Local	0.03%	0.39%		0.23%	0.12	0.34
Industry	1.41%	-3.96%		1.11%	1.27	3.53
Country	0.43%	-3.96%		0.95%	0.45	1.26
Currency	0.00%	0.00%		0.72%	0.00	-0.01

*Risk Model: WW4AxiomaMH; Long Only

Stock selection is positive, 37 basis points, though it has fallen since the initial (2017) publication, and is no longer statistically significant. MCM Management (MCM) is a global growth specialist and one would expect positive exposures to growth and medium-term momentum. The exposure to growth has lost the portfolio 16 basis points whereas the medium-term momentum exposure produced 335 basis points of factor contribution. ²⁴

MCM has managed a Non-U.S. Growth portfolio for over 23 years. The portfolio has produced over 210 basis points, annualized, of Active Returns (no longer statistically significant, since-inception), see Table 4. Stock selection is positive, 44 basis points annualized, and is no longer statistically significant. MCM Management (MCM) is a global growth specialist and one would expect positive exposures to growth and medium-term momentum. The exposure to growth has lost the portfolio 12 basis points whereas the

Past performance is not indicative of future returns.

²⁴ While occasionally producing string short-term results (112'17 - H1'18), the Axioma Growth factor model is extremely weak, being based on historical earnings and sales growth. Its information coefficient is approximately one-quarter of the CTEF information coefficient, and the Axioma growth factor index is not statistically significant.



medium-term momentum exposure produced 194 basis points of factor contribution. ²⁵The reader

immediately sees that the EM portfolio produces more than 150 basis points of medium-term momentum

returns than the Non-U.S. portfolio.

Table 4: XUS Attribution vs. MSCI ACW Ex U.S. Growth Index FACTOR ATTRIBUTION: FACTOR CONTRIBUTION

McKinley Capital Non-U.S. Growth Representative Portfolio

Period: 12-31-1996 through 12-31-2018 Currency: United States Dollar

		Avg		Re alize d	Information	
Source of Return*	Contribution	Exposure	Hit Rate	Risk	Ratio	T-Stat
Portfolio	7.69%			18.61%		
Benchmark (MSCI ACW Ex U.S. Growth Index)	5.57%			17.05%		
Active	2.12%	>		7.08%	0.30	1.40
Specific Return	0.44%	>		5.55%	0.08	0.37
Factor Contribution	1.68%			4.35%	0.38	1.80
Style	1.62%			2.21%	0.73	3.43
Dividend Yield	-0.01%	-0.00117	53.03%	0.15%	-0.08	-0.36
Earnings Yield	0.15%	0.09820	60.23%	0.24%	0.63	2.96
Exchange Rate Sensitivity	0.00%	-0.00307	49.24%	0.15%	-0.03	-0.14
Growth	-0.12%	0.13867	44.70%	0.24%	-0.49	-2.29
Leverage	0.07%	-0.00113	50.00%	0.20%	0.35	1.65
Liquidity	0.06%	0.09501	53.79%	0.39%	0.16	0.75
Market Sensitivity	-0.16%	0.04809	47.35%	0.72%	-0.23	-1.07
Medium-Term Momentum	1.94%	0.40076	70.45%	1.65%	1.18	5.52
Profitability	-0.09%	-0.04768	50.00%	0.26%	-0.35	-1.66
Size	-0.04%	-0.08946	50.00%	1.09%	-0.03	-0.16
Value	0.19%	0.06665	57.20%	0.22%	0.89	4.18
Volatility	-0.38%	0.06713	44.70%	0.64%	-0.59	-2.77
Market	-0.62%	-8.98%		2.47%	-0.25	-1.18
Local	-0.01%	0.00%		0.02%	-0.60	-2.81
Industry	0.24%	-8.98%		1.74%	0.14	0.66
Country	0.07%	-8.98%		2.68%	0.03	0.13
Currency	0.37%	0.00%		2.08%	0.18	0.84

*Risk Model: WW4AxiomaMH; Long Only

In full disclosure, the EM portfolio is officially benchmarked versus the EM Growth benchmark and its corresponding Active, Specific, and Momentum Returns are 353, 29, and 263 basis points, respectively. Active returns are still statistically significant versus its official benchmark, see Table 5.

Past performance is not indicative of future returns.

²⁵ The Non-US portfolio has implemented an EAW1.2 strategy, with an Active weight averaging 120 basis points, rather than a full strategy, EAW2, and the lack of risk exposure has led to lower Specific Returns during the 2010-2018 time period.

^{*}The period chosen in table 4 was due to the actual inception date (10/01/95) pre-dating the existence of the ACW ex US Growth Index



Table 5: EM Attribution vs MSCI EM Growth Index FACTOR ATTRIBUTION: FACTOR CONTRIBUTION McKinley Capital Emerging Markets Growth Representative Portfolio

Period: 03-31-2011 through 12-31-2018

Currency: United States Dollar

	Avg		Realized	Information	
Contribution	Exposure	Hit Rate	Risk	Ratio	T-Stat
5.09%			16.72%		
1.56%			16.76%		
3.53%	>		4.93%	0.72	1.99
0.29%	>		4.07%	0.07	0.20
3.24%			2.66%	1.22	3.39
3.19%			1.54%	2.07	5.76
0.14%	0.17714	61.29%	0.14%	1.01	2.81
0.12%	0.14914	59.14%	0.18%	0.68	1.90
0.03%	0.06310	60.22%	0.06%	0.51	1.41
0.02%	0.07108	46.24%	0.09%	0.17	0.46
0.02%	-0.07933	49.46%	0.08%	0.23	0.64
-0.05%	0.04581	49.46%	0.09%	-0.60	-1.66
0.16%	-0.10319	52.69%	0.56%	0.29	0.80
2.63%	0.54187	74.19%	1.37%	1.93	5.36
0.22%	0.09505	72.04%	0.12%	1.91	5.32
0.37%	-0.12172	62.37%	0.40%	0.94	2.61
0.00%	0.00800	45.16%	0.10%	0.02	0.06
-0.48%	0.12266	37.63%	0.42%	-1.15	-3.21
-0.34%	-3.90%		0.46%	-0.75	-2.09
0.03%	0.71%		0.23%	0.11	0.31
-0.02%	-3.90%		0.57%	-0.04	-0.11
0.36%	-3.90%		0.93%	0.39	1.08
0.03%	0.00%		0.73%	0.04	0.10
	Contribution 5.09% 1.56% 3.53% 0.29% 3.24% 3.19% 0.14% 0.12% 0.03% 0.02% 0.02% 0.02% 0.02% 0.05% 0.16% 2.63% 0.22% 0.37% 0.00% -0.48% 0.03% -0.02% 0.36% 0.03%	Avg Contribution Exposure 5.09% 1.56% 1.56% 3.53% 0.29% 3.24% 3.19% 0.1491 0.14% 0.17714 0.14% 0.17714 0.12% 0.14914 0.03% 0.06310 0.02% 0.07108 0.02% 0.07108 0.02% 0.07108 0.02% 0.07108 0.02% 0.04581 0.16% 0.0319 2.63% 0.54187 0.22% 0.09505 0.37% -0.12172 0.00% 0.00806 -0.34% 0.12266 -0.34% 0.12260 -0.03% 0.71% -0.02% -3.90% 0.03% -3.90% 0.36% -3.90%	Avg Contribution Exposure Hit Rate 5.09% 1.56% 1.56% 3.53% 0.29% 1.56% 3.53% 0.29% 1.56% 3.53% 0.29% 1.56% 3.53% 0.29% 1.56% 3.19% 0.101% 61.29% 0.14% 0.17714 61.29% 0.12% 0.14914 59.14% 0.03% 0.06310 60.22% 0.02% 0.07108 46.24% 0.02% 0.07133 49.46% 0.02% 0.07933 49.46% 0.02% 0.04581 49.46% 0.16% 0.10319 52.69% 2.63% 0.54187 74.19% 0.22% 0.09505 72.04% 0.12% 0.02006 45.16% 0.037% 0.1226 37.63% 0.034% 0.71% -0.02% 0.035% 0.71% -0.02% 0.36% -3.90% 0.036%	AvgRealizedContributionExposureHit RateRisk 5.09% 16.72% 1.56% 16.76% 3.59% 4.93% 0.29% 4.07% 3.24% 2.66% 3.19% 1.54% 0.14% 0.17714 0.14% 0.17714 0.12% 0.14914 0.03% 0.06310 0.02% 0.07108 46.24% 0.09% 0.02% 0.07108 45.24% 0.09% 0.02% 0.07933 49.46% 0.08% -0.05% 0.04581 49.46% 0.09% 0.16% -0.10319 52.69% 0.56% 2.63% 0.54187 74.19% 1.37% 0.22% 0.09505 72.04% 0.12% 0.37% -0.12172 62.37% 0.40% 0.03% 0.71\% 0.03% 0.71\% 0.23% 0.57% 0.36% -3.90\% 0.03% 0.00\% 0.03% 0.00\%	AvgRealizedInformationContributionExposureHit RateRiskRatio 5.09% 16.72% 1.56% 16.76% 3.53% 4.93%0.72 0.29% 4.07%0.07 3.24% 2.66%1.22 3.19% 1.54%2.07 0.14% 0.171461.29%0.14% 0.12% 0.1491459.14%0.18%0.68 0.03% 0.0631060.22%0.06%0.51 0.02% 0.0710846.24%0.09%0.17 0.02% 0.0710849.46%0.08%0.23 -0.05% 0.0458149.46%0.09%-0.60 0.16% -0.1031952.69%0.56%0.29 2.63% 0.5418774.19%1.37%1.93 0.22% 0.0950572.04%0.12%1.91 0.37% -0.1217262.37%0.40%0.94 0.00% 0.028045.16%0.10%0.02 0.48% 0.1226637.63%0.42%-1.15 -0.34% -3.90%0.57%-0.040.36% 0.03% 0.71%0.23%0.11-0.02% -0.02% -3.90%0.57%-0.04 0.36% -3.90%0.93%0.39 0.03% 0.00%0.73%0.04

*Risk Model: WW4AxiomaMH; Long Only

As a Quantitative (Quant) asset manager, we believe that success requires achieving statistically significant Active and Factor Returns as well as positive (and hopefully statistically significant stock returns, or Specific Returns). Most managers use a secondary benchmark of their peers, as one would find in the evestment universe of managers. In the case of the MCM EM portfolio, we are still in the top 10% since-inception and in the top quintile for the past five-years, see Table 6. The MCM Non-U.S. portfolio, with an AUM exceeding \$2 billion, is in the top two quintiles for 5-years and in the top half since-inception, see Table 7. The Non-U.S. universe benchmark is at the 97th percentile (almost everyone beats the benchmark); whereas the EM benchmark is at the 73rd percentile.²⁶

Past performance is not indicative of future returns.

²⁶ We reported on strategies of one-half the MCM AUM in this analysis. The five-year AUM-weighted Specific Returns were approximately 31 basis points, through 9/30/2018. We know our clients require more; perhaps as much as 75 basis points of Specific Returns.



X. SUMMARY AND CONCLUSIONS AND A LOOK TO THE FUTURE

Markowitz mean-variance optimization continues to be particularly efficient for producing efficient frontiers for the 2003 – 2018 time period. We show how forecasted earnings acceleration produces highly statistically significant stock selection in global and U.S. stock universes. CTEF 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) and Guerard et al. (2013) published their studies? No, CTEF and REG10 still dominate most other models, including the 36 models tested in Guerard et al. (2018), including the Post-Global Financial Crisis.

Guerard et al. (2018) also show that updated models pass the Level III Data Mining Corrections test of Markowitz and Xu (1994) for statistical significance. Models will never be perfect, but their portfolios can be statistically significant. Models that fail such a result may offer investors several years of returns, but the authors believe that models that do not pass Level II and III tests will rarely produce statically significant five-year and since-inception Active Returns and positive Specific Returns. Malkiel (1973 and 2003) has argued that there are no free lunches, that mutual funds underperformed the S&P 500 Index for the 1981 -2001 time period, and there will be no \$100 bills around the stock exchanges for long. Are markets efficient? No, not completely but significant databases, computers, and thinking caps are required to outperform.

Now-classical financial anomalies, as identified in Dimson (1988), Jacobs and Levy (1988), and Levy (1999), exist and have persisted. Levy (2012) confirmed his findings on financial anomalies. Moreover, the recent findings of Gillam, Guerard, and Cahan (2015) suggest that earnings transcripts, commonly available to investors and often reported in the news, contain information that offers statistical support for inclusion in the portfolio creation process. Alternative data and predictive analytics, new data sources and modeling techniques, offer the potential for investor risk-adjusted return enhancement. Evidence suggests that about 2 in 20 new databases enhancement the financial anomalies we report. Thus,



we see the possibility for about 15-20 percent return enhancement with more sophisticated robust regression, machine learning, and the new databases. If these patterns in returns persist for the next 5- 10 years at that order of magnitude based on widely available sources of information and technologies, it would clearly be relevant to institutional and individual investors alike, who should account them in their financial plans and portfolio allocations. Individuals would rationally incorporate additional risk premia in the management of their assets and liabilities inherent in their financial plans. Institutions would re-sell these exposures to investors seeking to do so. If these patterns are truly anomalous, however, investors would do well to avoid being on the other side of the trades that give away alpha to others in the market and destroy their best-laid plans.

Future research on performance will lead to consider examine the CRSP database of mutual fund to see how our strategies perform relative to mutual funds, a test of the strong form of the EMH. Portfolio implementation requires a constant mentality of conviction toward complete and full model implementation. Do not report an MVTaR strategy and expect an EAW1 strategy to produce similar Active returns and Information Ratios. A final word should be said with respect to the CRSP mutual fund database. Portfolio returns and standard deviations are available on the evestment universes. However, one cannot calculate Active Returns and Specific Returns on evestment individual portfolios as one can mutual funds using the mutual fund database. The authors believe that a 31basis point average on AUM may be extremely competitive relative to the CRSP mutual fund database during the past five years.

Past performance is not indicative of future returns.



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31

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Fees are billed monthly or quarterly, which produces a compounding effect on the total rate of return net of management fees. As an example, the quarterly effect of investment management fees on the total value of a client's portfolio assuming (a) \$1,000,000 investment, (b) portfolio return of 5% a year, and (c) 1.00% annual investment advisory fee would be \$10,038 in the first year, and



cumulative effects of \$51,210 over five years and \$110,503 over ten years. Actual client fees vary. A fee schedule, available upon request, is described in the firm's Form ADV part 2A.

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Appendix: Robust Regression

The proc robustreg, one can use the Huber (1973) M estimation procedure, the Rousseeuw (1984) Least Trimmed Squares (LTS), the Rousseeuw and Yohai (1984) S procedure, or Yohai (1987) MM estimation procedure. We will report iterations of these procedures in Chapter 4 as we simulate various robust regression investment strategies to maximize portfolio returns. In this appendix, we will dive deeper into the Huber Maud MM procedure that we use on a daily basis for portfolio construction.

The Huber M estimation procedure does not maximize the sum of the squared errors, but rather the sum of the residuals as stated:

$$Q(\theta) = \sum_{i=1}^{n} \rho\left(\frac{r_i}{\sigma}\right) \tag{A-1}$$

where $r = y - x\theta$ and p is the quadratic function, Huber (1973, 1981) held that robust procedure should be "optimal or nearly optimal", be robust in the sense that small deviations from the model assumptions only slightly impair the asymptotic variance of the estimate, and larger deviations from the model should not cause a "catastrophe" (Huber, 1981, p.5). Huber was concerned with efficiency of the parameter estimated. Robustness means insensitivity to small deviations from model assumptions and the minimizations off the degradation of performance for ε – deviations from the assumptions. Let T_n be an estimate

$$\sum \rho(x_i; T_n) = min! \tag{A-2}$$

or

$$\sum \psi (x_i; T_n) = 0$$
 (A-3)

where

$$\psi(x;\,\theta) = \frac{d}{d\theta}\rho(x;\theta) \tag{A-4}$$

In the case of linear fitting of (A-1), the first order conditions are

$$\sum_{i=1}^{n} \psi\left(\frac{r_{i}}{\sigma}\right) x_{ij} = 0, j = 1, \dots, \rho$$
(A-5)

Proc robust regression solves (A-18) by iteratively reweighted least squares with the weight function

$$w(x) = \frac{\psi(x)}{x}$$
(A-6)

The σ in (A-18) is unknown and must be estimated. Huber (1973) modify objection function (A-14) as

$$Q(\theta,\sigma) = \sum_{i=1}^{n} \left[\rho\left(\frac{r_i}{\sigma}\right) + a \right] \sigma$$
(A-7)



and $\hat{\sigma}$ is estimated by Huber (1973) as:

$$(\sigma^{m+1})^2 = \frac{1}{nh} \sum_{i=1}^n X_d \left(\frac{r_i}{\hat{\sigma}^{(m)}}\right) (\hat{\sigma}^{(m)})^2$$
where
$$(x^2 - 1 + 1) = 1 \frac{d^2}{d^2}$$
(A-8)

$$X_{d}(x) = \begin{cases} \frac{x}{2}, & |x| < d \frac{u}{2}, \\ 0, & otherwize. \end{cases}$$
(A-9)

An alternative to the Huber weighting function is the Beaton-tweeny (1974) bisquare function where σ is solved from: $\frac{1}{n-p}\sum X_d \left(\frac{r_i}{\sigma}\right) = \beta$ (A-210)

with

$$X_d(x) = \frac{3x^2}{d^2} - \frac{3x^4}{d^4} + \frac{x^6}{d^6}$$

If |x| < d otherwise $\beta = fX_d d\phi(s)$

What we need is a King's English explanation. The bisquare and Huber M estimation weight functions map the sensitivity of the robust estimator to the outlier value. The modeler can identify outliers, or influential data, and re-run the ordinary least squares regressions on the re-weighted data, a process referred to as robust (ROB) regression. In ordinary least squares, OLS, all data is equally weighted. The weights are 1.0. In robust regression one weights the data inversely with its OLS residual; i.e., the larger the residual, the smaller the weight of the observation in the robust regression. In robust regression, several weights may be used. We will review the Beaton – Tukey (1974) bisquare iteratively weighting scheme. The intuition is that the larger the estimated residual, the smaller than weight. The Beaton – Tukey bisquare, or biweight criteria, for re-weighting observations is:

$$w_{i} = \begin{cases} (1 - (\frac{|e_{i}|}{\sigma_{\varepsilon}}/4.685^{2})^{2}, & if \ \frac{|e_{i}|}{\sigma_{\varepsilon}} \ge 4.685, \\ 0, & if \ \frac{|e_{i}|}{\sigma_{\varepsilon}} < 4.685. \end{cases}$$
(A-11)



Table 1: APT MVTaR Portfolio Attributions run in Axioma

Universe: MSCI All Country World Growth

Time Period of Simulation:31-DEC-2002 to 31-DEC-2014

	Port	folio	Bench	nmark		Acti	ive			Spe	cific			Industry	
	Return	Risk	Return	Risk	Return	Risk	IR	T-Stat	Return	Risk	IR	T-Stat	Return	Exposure	T-Stat
MVTUKEY99LL_1	13.05%	16.03%	9.22%	15.64%	3.83%	2.43%	1.58	5.46	1.30%	1.61%	0.80	2.78	-0.27%	0.00	-1.17
MVTUKEY99LL_100	19.25%	19.85%	9.22%	15.64%	10.03%	7.14%	1.40	4.86	4.42%	3.80%	1.16	4.02	-0.37%	0.00	-0.68
MVTUKEY99LL_200	20.86%	20.15%	9.22%	15.64%	11.64%	7.77%	1.50	5.19	5.61%	4.34%	1.29	4.48	-0.14%	0.00	-0.25
MVTUKEY99LL_500	21.85%	20.52%	9.22%	15.64%	12.63%	8.28%	1.53	5.28	6.20%	4.60%	1.35	4.66	0.01%	0.00	0.02
MVYOHAI99L_1	13.23%	16.03%	9.22%	15.64%	4.01%	2.48%	1.61	5.59	1.47%	1.67%	0.88	3.05	-0.32%	0.00	-1.33
MVYOHAI99L_100	20.47%	19.44%	9.22%	15.64%	11.25%	6.69%	1.68	5.82	5.86%	3.60%	1.63	5.64	-0.22%	0.00	-0.40
MVYOHAI99L_200	21.31%	19.68%	9.22%	15.64%	12.09%	7.19%	1.68	5.82	6.30%	3.93%	1.60	5.55	-0.24%	0.00	-0.42
MVYOHAI99L_500	21.91%	20.00%	9.22%	15.64%	12.69%	7.72%	1.64	5.70	6.85%	4.23%	1.62	5.61	-0.10%	0.00	-0.17

		Momentum			Value			Growth			Profitability	
	Return	Exposure	T-Stat	Return	Exposure	T-Stat	Return	Exposure	T-Stat	Return	Exposure	T-Stat
MVTUKEY99LL_1	0.76%	0.11	5.63	0.79%	0.27	6.13	0.01%	0.00	0.54	0.01%	-0.02	0.51
MVTUKEY99LL_100	2.82%	0.36	6.73	1.56%	0.51	5.36	-0.15%	0.12	-3.23	0.11%	-0.02	1.99
MVTUKEY99LL_200	3.14%	0.39	7.16	1.50%	0.50	5.11	-0.17%	0.12	-3.54	0.20%	0.00	3.56
MVTUKEY99LL_500	3.34%	0.40	7.57	1.51%	0.51	4.93	-0.19%	0.12	-3.63	0.19%	0.00	3.55
MVYOHAI99L_1	0.73%	0.10	5.62	0.75%	0.28	5.85	0.01%	0.00	0.48	0.03%	-0.02	0.83
MVYOHAI99L_100	2.60%	0.35	6.68	1.36%	0.49	4.93	-0.10%	0.11	-2.51	0.19%	0.01	3.17
MVYOHAI99L_200	2.89%	0.37	7.19	1.41%	0.49	4.94	-0.10%	0.13	-2.50	0.22%	0.01	3.52
MVYOHAI99L_500	3.03%	0.38	7.40	1.44%	0.50	4.95	-0.14%	0.14	-3.13	0.21%	0.02	3.64

		Size		Di	vidend Yield	1		Earnings Yie	ld		Volatility	
	Return	Exposure	T-Stat	Return	Exposure	T-Stat	Return	Exposure	T-Stat	Return	Exposure	T-Stat
MVTUKEY99LL_1	0.69%	-0.21	2.89	0.18%	0.25	1.85	0.23%	0.31	2.13	-0.14%	0.02	-1.90
MVTUKEY99LL_100	2.46%	-0.65	3.65	0.44%	0.36	2.23	0.44%	0.52	2.31	-2.15%	0.30	-6.60
MVTUKEY99LL_200	2.59%	-0.67	3.74	0.46%	0.36	2.19	0.46%	0.53	2.33	-2.43%	0.33	-6.93
MVTUKEY99LL_500	2.61%	-0.68	3.73	0.45%	0.37	2.17	0.45%	0.54	2.26	-2.58%	0.34	-7.03
MVYOHAI99L_1	0.69%	-0.21	2.98	0.18%	0.26	1.77	0.25%	0.33	2.22	-0.07%	0.01	-1.08
MVYOHAI99L_100	2.43%	-0.65	3.61	0.42%	0.39	2.09	0.50%	0.56	2.49	-2.06%	0.29	-6.51
MVYOHAI99L_200	2.55%	-0.67	3.65	0.45%	0.40	2.04	0.50%	0.57	2.45	-2.22%	0.31	-6.48
MVYOHAI99L_500	2.60%	-0.67	3.73	0.44%	0.41	2.10	0.55%	0.59	2.58	-2.33%	0.32	-6.68

Where MV = Mean - Variance Portfolios

Tukey99, Yohai99 = Lambda Tilt; i.e.,

1 = index – replication; 200 = Sharpe Ratio and Information Ratio maximizing lambda. The Tukey99 and Yohai99 represent 99% efficiency in the parameters.

Past performance is not indicative of future returns.



Table 6 McKinley Capital Management, LLC Emerging Markets Growth

Preferred Benchmark MSCI EM Growth-GD Primary Universe Product Inception Date 03/25/2011

eVestment Global Emerging Mkts Equity



5 Years Since Inception 7.75 Years Rk Rk 5th percentile 5.49 4.49 25th percentile 3.48 2.56 Median 2.28 1.22 75th percentile 1.38 0.24 95th percentile -0.51 -1.11 # of Observations 418 278 Emerging Markets Growth 3.85 19 3.95 10 MSCI EM Growth-GD 2.92 1.48 33 45 MSCI EM-GD 2.03 57 0.35 73 MSCI EM Value-GD 1.02 -0.87 82 93

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Table 7 McKinley Capital Management, LLC Non-U.S. Growth

Preferred Benchmark Primary Universe Product Inception Date MSCI ACWI ex-US Growth-GD eVestment ACWI ex-US Equity 10/01/1995



	5 Years	7.75 Years		Since Inception 23.25 Y	ears
	F	tk	Rk		Rk
5th percentile	6.05	7.40		9.49	
25th percentile	3.15	5.15		8.13	
Median	1.65	3.74		7.01	
75th percentile	0.67	2.54		6.23	
95th percentile	-0.95	1.27		5.50	
# of Observations	296	232		43	
Non-U.S. Growth	2.34	3.35	56	7.19	45
MSCI ACWI ex-US Growth-GD	2.06	42 3.06	64		
MSCI ACWI ex-US-GD	1.14	52 2.43	77	5.12	97
MSCI ACWI ex-US Value-GD	0.18 8	33 1.77	91		



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Table 8: Factor IC Performance, Non-US and EM Universes, 5-Year and 10-Year (post-GFC) Periods, as of December 2018. *Past performance is not indicative of future returns*.



Chart 1: Optimization Chart MCM Portfolio Construction and Modeling Process





Chart 2:

Manager Performance

January 2003 - December 2014 (Single Computation)



Where MV = Mean - Variance Portfolios

CTEF, Tukey99, Yohai99 = Lambda Tilt; i.e.,

1 = index - replication; 200 = Sharpe Ratio and Information Ratio maximizing lambda. The Tukey99 and Yohai99 represent 99% efficiency in the parameters.

Past performance is not indicative of future returns.

