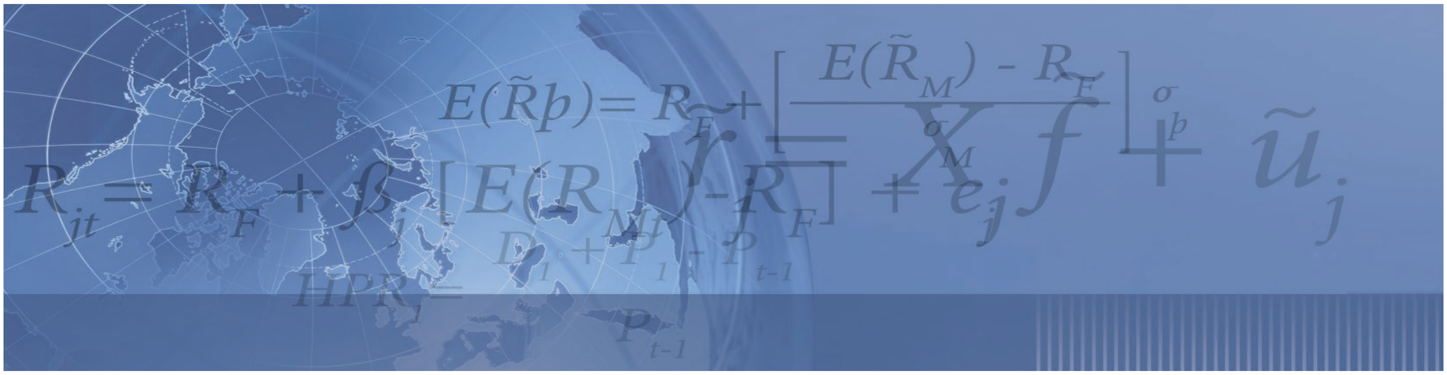

The Existence and Persistence of Financial Anomalies

John Guerard, McKinley Capital Management, LLC
Anchorage, AK 99503
(JGuerard@mckinleycapital.com)

Harry Markowitz, Harry Markowitz & Company
San Diego, CA

Abstract

Financial anomalies have been studied for over 80 years in the U.S. Have the anomalies changed and are they persistent? Graham and Dodd put forth the "Low PE" strategy in 1934. Does the "Low PE' strategy still work and how often does it work? Historic earnings are (still) highly statistically associated with stock returns. Earnings forecasting data has been a consistent, and highly statistically significant, source of excess returns. If one started a career on Wall Street during the 1987 - 1991, what might one have known? Dimson (1988), and Jacobs and (Ken) Levy (1988), identified a (large) set of 20-plus variables that produced statistically significant excess returns and were reported as anomalies. Haugen (1999) and (Haim) Levy (1999) reported a (large) set of 20-plus variables that produced statistically significant excess returns and were very similar to the Dimson and Jacobs and Levy set of variables. The reported financial anomalies of the 1988s continued to be recognized and tested through the 1990s. We test a large set of U.S. and global variables over the past 16 years. We report that many of these fundamental, earnings forecasts, revisions, and breadth, Momentum, and cash deployment strategies that maintained their statistical significance during the 2003-2018 time period and have dominated other financial variable datasets in the post-Global Financial Crisis time period. Moreover, the earnings forecasting model excess returns are greater in Non-US and Global markets than in the U.S. markets. The anomalies variables are highly statistically significant in its post-publication time period, including booms, recessions, and highly volatile market conditions. We report that quantitative-based models, built on anomalies known at the time, have outperformed indexes in over 70 -80% of the years. Is that enough for investors? Should that be enough for investors?

The purpose of this study is to document the existence, persistence, and effectiveness of variables reported as financial anomalies during the 1988-1999 time period and test whether these reported anomalies are statistically significant during the 1986–2017 and 2003-2017 time periods. One must create optimal portfolios to assess the predictive power of financial anomalies. The reader of Management Science has seen many of the outstanding financial investing applications from the Martin (1955) and Baumol (1963) application of the original Markowitz portfolio selection process. Sharpe (1963) and Fama (1965) presented applications of the Sharpe Diagonal model. Sharpe (1971), Levy and Samuelson (1972), and Konno (1991) presented variations on the Capital Asset Pricing Model (CAPM). Lehmann and Modest (2005), Zhang (2009), and Brennan and Lo (2010) multi-factor (APT) applications. The reader of Management Science has seen significant financial treatments, such as Hirshleifer, Hou, and Teoh (2012) in the two-part special issue on behavioral economics and finance, edited by Barber, Ho, and Odean, and earnings forecasting analysis in Ball and Ghysels (2018). This research analysis specifically addresses forecasting and balance sheet anomalies reported in the earnings forecasting applications of Elton and Gruber (1972), Elton, Gruber, and Gultekin (1981), and the managerial finance planning model applications of McInnes and Carleton (1982) and Guerard, Bean and Stone (1989). What do we add to an extensive anomalies literature? We test portfolio anomalies in a post-publication setting. We report three results: (1) many of the reported financial anomalies published in 1988 – 1999 time period maintained their statistical significance active (or excess) returns; (2) the anomalies are greater in non-U.S. markets than in the U.S.; and (3) transactions costs do not destroy the excess returns. Our anomalies results continue to cast serious doubt on the semi-strong of the Efficient Markets Hypothesis.

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, 1991). 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. The author will report highly 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 a 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

$f_m(p_1, t+\tau, \ldots, p_n, t+\tau \mid \Phi^m$ = 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:

$$\tilde{R}_{jt} = \frac{\widetilde{p_j}_{\,t} - p_{j\,,\,t-1}}{p_{j\,,\,t-1}} \tag{2}$$

Stock return is given by:

$$E_m(\tilde{R}_{jt} \mid \Phi_{t-1}) = \frac{\widetilde{p_j}_{\,t} \mid \Phi_{t-1}^{m} - p_{jt}}{p_{j\,,\,t-1}} \tag{3}$$

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 CAPM relationship of risk and return to establish the tests of the value of public information.

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

$$\beta = \frac{cov\,(\tilde{R}_j\,, \tilde{R}_m)}{\sigma^2\,\tilde{R}_{mt}} \tag{5}$$

$$\alpha_j = E(\tilde{R}_{jt} \mid \Phi_{t-1}) - \beta_j\, E(R_{mt} \mid \Phi_{t-1}) \tag{6}$$

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

For efficiency:

$$E(\varepsilon_{jt} \mid \Phi_{t-1}, R_{mt}) = 0 \tag{8}$$

Traditional fundamental variables, such as earnings-to-price, book value-to-price, cash flow-to-price, sales-to-price, cash flow-to-price, small size, institutional holdings, earnings forecasts, revisions, recommendations, and breadth, earnings surprises, insider trading, dividend yield, momentum were variables identified in Dimson (1988), Jacobs and (Ken) Levy (1988), and (Haim) Levy (1999) as anomalies. We report the hypothesized, tested, and verified anomalies in Table 1. Bloch, Guerard, Markowitz, Todd, and Xu (1993), Ziemba and Schwartz (1993), Chan, Hamao, and Lakonishok (1991), and Haugen and Baker (1996) specifically addressed many of the earlier reported non-U.S. anomalies and /or compared U.S. and non-U.S. anomalies. Testing and reporting on financial anomalies in October 2018, we find that many of the Jacobs and Levy, Levy, Bloch, Guerard, Markowitz, Todd, and Xu, Ziemba and Schwartz, Chan, Hamao, and Lakonishok, and Haugen

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

and Baker variables have continued to produce statistically significant Active and Specific Returns in the post-publication period, 2003 – 2017 (and later) time periods. 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. The model has worked in booms, recessions, and highly volatile market conditions. This study is composed of four sections. the first section addresses what we knew in 1987-1991, with regard to reported fundamental data, 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 first section is a brief literature review of the fundamental variables used in our composite models. The second section is a brief literature review of the fundamental variables, the earnings forecasting models, and the price momentum variables used in our expanded composite models. The third section examines the 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.

1. WHAT WE KNEW IN 1991 TESTS OF FUNDAMENTAL DATA

In 1991, Harry Markowitz developed an equity research group, DPOS, 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. What did we know in 1991? The reader is referred to Table 1 where we discuss the state of the art of financial anomalies. The DPOS Group was well-versed in the low PE or high earnings-to-price, EP, high book value-to-price, high cash flow-to-price, high sales-to-price, net current asset value, and the earnings forecasting models in Graham and Dodd (1934), Graham, Dodd, and Cottle (1962), Elton and Gruber (1972a, 1972b), Latane, Tuttle and Jones (1975), and Dimson (1988).[2] Graham and Dodd and Graham (1973) 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. 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. DPOS built stock selection models and created Markowitz Mean-variance Efficient Frontiers for US and Japanese stock markets. 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. 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, but 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.

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 (9) to assess empirically the relative explanatory

[2] 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.

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.

$$TR = w_0 + w_1 EP + w_2 BP + w_3 CP + w_4 SP + w_5 REP + w_6 RBP + w_7 RCP + w_8 RSP + e_t \quad (9)$$

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]; and

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; the presence of highly correlated variables (latent root regression to address the issue of the highly correlated variables, known as 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 robust regression techniques, inputting the expected return forecasts produced by each method into a mean-variance optimizer. The robust regression-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 multicollinearity is important. Second, Bloch et al. (1993) quantified the survivor bias (including dead companies in the database) 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.[3] 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.

2. WHAT WE KNEW IN 2002 and 2012 TESTS OF FUNDAMENTAL, EXPECTATIONS, AND PRICE MOMENTUM DATA

Studies of the effectiveness of corporate earnings forecasting variables, reported in Cragg and Malkiel (1968), Elton and Gruber, and Gultekin (1981), Hawkins, Chamberlain, and Daniel (1984), DeBondt and Thaler (1989), Wheeler (1991), and Guerard and Stone (1992) were reprinted in Bruce and Epstein (1994).[4] Analysts'

[3] 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.

[4] 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 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.

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, 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. The studies reprinted in Bruce and Epstein (1994) and Guerard, Gultekin and Stone (1997) reported that analysts' forecast variables enhanced portfolio returns over the long-run. By 1999, we knew that CTEF, a composite model of earnings forecasts, revisions, and breadth, the agreement among analysts' revisions, was highly statistically significantly correlated with stock returns. Guerard and Mark (2003) published that CTEF, and a nine-factor model of REG8 plus CTEF was also highly (statistically) significantly correlated with stock returns. Would these financial anomalies continue?

There is an equally extensive body of literature on 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).[5] Influential recent researchers such as Conrad and Kaul (1993), Conrad and Kaul (1998), and Lo, Mamaysky, and Wang (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

Guerard and Stone (1992), Womack (1996) Guerard, Gultekin and Stone (1997), Hong, Kubik, and Solomon (2000), Hong and Kubik (2003), Guerard, Markowitz, and Xu (2015), and Ball and Ghysels (2018), are among the thousands of studies of analysts' forecasting efficiency and how analysts' forecasts enhance portfolio returns.

[5] 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.

periods.[6] Jagadeesh and Titman (1993) constructed portfolios based on six-months of positive price momentum, held the portfolios for six months, and earned 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, Markowitz, and Xu (2014) added the Guerard and Mark (2003) 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.[7] Guerard, Rachev, and Shao (2013) and Guerard and Mark (2018) applied the 10-factor model to global stocks, referring to the model as GLER, or REG10. See equation (10).

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

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];

[6] 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.
[7] Bush and Boles (1983) and Brush (2001) tested a PM121 price momentum variable, defined as P(t-1)/P(t-12).

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. Guerard and Mark (2018) updated the GLER model simulation period to the 1996 – 2016 time period. The GLER model produced highly statistically significant active returns and better stock selections than the USER model over the corresponding period. [8] The earnings forecasting model, CTEF, continued to produce statistically significant Active Returns and Specific Returns (stock selection) during the 1996 -2016 time period. The I/B/E/S database continues to be a great source of statistically significant excess returns for stocks.

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

3. MARKOWITZ RISK MODELING AND AXIOMA RISK MODELS: CONSTRUCTING MEAN-VARIANCE EFFICIENT FRONTIERS

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

[8] 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.

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.

$$E(R_p) = \sum_{i=1}^{N} x_i E(R_i) = \sum_{i=1}^{N} x_i \mu_i \qquad (11)$$

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} x_i\, x_j c_{ij} \qquad (12)$$

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

$$minimize_{\{x_i \geq 0, x_i \leq \bar{u}\}} \;\; x^T C x - \lambda \mu^T x \qquad (13)$$

where λ is the risk-return tradeoff parameter and $\bar{u}$ is the fixed upper bound. Bloch, Guerard, Markowitz, Todd, and Xu (1993) created efficient frontiers using a purely full historical covariance matrix.

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:

$$R_j = \sum_{k=1}^{K} \beta_{jk} \widetilde{f_k} + \widetilde{e_j}. \qquad (14)$$

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.[9] 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,

[9] 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

$$C = \beta C_{f,f} \beta' + \Sigma. \quad (15)$$

If the investor is more concerned about tracking a particular benchmark, the mean-variance optimization in Eq. (13) can be reformulated as a mean-variance tracking error at risk (MVTaR) optimization:

$$\text{minimize } (x - x_b)^T C (x - x_b) - \lambda \mu^T (x - x_b) \quad (16)$$

where x_b is the weight vector of the benchmark.

In 1975, Barr Rosenberg and his associates introduced the BARRA US Equity Model, often denoted USE1.[10] 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

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).

[10] 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). Rosenberg and Marathe (1979), Rudd and Rosenberg (1979), and Rudd and Clasing (1982) are excellent references 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.

descriptor is scaled such that its value is one standard 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.[11] 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 model.

Another commercially-available risk model is the Axioma Risk Model. The Axioma Robust Risk Model[12] 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 of constant variance; 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. 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.

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

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

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 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.[13]

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

[13] 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.[13] 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.

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

$$C_{new} = C + \sigma_{\underline{\alpha}}^2 \underline{\alpha} \cdot \underline{\alpha'} + \sigma_{\underline{\gamma}}^2 \underline{\gamma} \cdot \underline{\gamma'} \,, \tag{17}$$

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 $\{4\%, 5\% \ldots 8\%\}$. 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 alpha is not aligned with the risk factors. The alignment characteristics of the implied alpha are much better than those of the alpha. 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.[14] 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.[15] 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

[14] 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.

[15] 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.

efficient trade-off curves than fundamentally-based risk model using our variables.[16] 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.

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[16]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. 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.

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, 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". 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). 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.

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4. THE EXISTENCE AND PERSISTENCE OF FINANCIAL ANOMALIES, 2003 -2106

Guerard et al. (2015) reported three levels of testing investment strategies.[17] 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. We seek to maximize the Geometric Mean (GM), Information Ratios(IRs), and Sharpe Ratios (ShRs). We rank our variables, low to high, 99 is preferred.

How often should portfolios turnover? Bloch et al. (1993) argued for lower turnover to maximize the Geometric Mean. Guerard and Mark (2018) agreed, reporting that monthly turnover of 10 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. Guerard and Mark (2018) reported monthly Axioma attribution statistics which, in the case of CTEF, indicates that the forecasted earnings acceleration variable loads on Medium-Term Momentum (0.257), Growth (0.151), and Value (0.469) and that Mean-variance CTEF and REG10 portfolios produced approximately 300-350 basis points of Specific Returns for the 20-year time periods. In the U.S.

[17] 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.

portfolios, equally-weighted 125 stock portfolios outperform Mean-variance (MV) four percent portfolios. [18] 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 reported that the only ranked CTEF variable produces statistically significant portfolio Active Total returns and Stock Specific Returns in the U.S. The CTEF, and REG10 portfolios produced statistically significant portfolio Active Total returns but insignificant Stock Specific Returns in U.S. stocks for the 1/2003 -11/2016 time period.

In the Non-U.S. and EAFE universes, Guerard and Mark (2018) reported that the CTEF ICs were higher than the REG10 or GLER ICs in their 10, 5, 3, and one-year time sub-periods. The CTEF and REG10 produced approximately 400-500 basis points of Active Returns and about 250 basis points of Specific Returns, see Table 30.9. The Non-U.S. portfolios offer more stock selection than U.S. portfolios with the addition of the REG8 plus CTEF (denoted REG9) and REG10 factors. The t-statistic on the risk stock selection effect in Non-U.S. portfolios is maximized with ranked CTEF. The t-statistics on the risk stock selection effect is statistically significant for 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. Guerard and Mark (2018) reported that only ranked CTEF is statistically significant in the U.S. whereas globally, ranked CTEF and REG10 are statistically significant in Total Active Returns and Risk Stock Selection Returns.

Global modeling for a "global growth specialist", such as McKinley Capital Management, LLC, involves the use of larger weighting of momentum and forecasted earnings acceleration factors. In this section, we report results for the top 7500 largest market-capitalized global stocks with at least two analysts' forecasts, 2003 – June 2018.

[18] 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.

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 costs[19]. We use two Mean-variance optimization techniques. First, the traditional mean-variance optimization technique found in Markowitz (1959), chapters 7 and 8. We refer to this full covariance matrix risk model as MVM59. Second, risk is measured by the mean-variance tracking error at risk, MVTaR where 20 orthogonal (Principal Components Analysis, PCA) betas are estimated. Our portfolio looks almost exactly like the market index benchmark, the MSCI All Country World index, on 20 dimensions. MVTaR maximizes returns while minimizing the underperformance of a index portfolio return. The optimization uses the ITG transactions costs curves discussed in Borkovec, Domowitz, Kiernan, and Serbin (2010).

In Table 2, report that with the CTEF variable, The MVM59, the traditional Markowitz (1959) mean-variance optimization analysis outperforms the MSCI All Country World benchmark. The Information Ratio, the ratio of portfolio Active (Excess) Return relative to the portfolio tracking error, TE, is maximized with a targeted tracking error of 8 percent, producing Active returns exceeding 6 percent and an Information Ratio (IR) of 0.63. The MVTaR portfolio substantially reduces risk and tracking error, TE. The MVTaR CTEF TE of 8 percent maximizes the Sharpe Ratio, the ratio of portfolio Active return relative to its standard deviation, its measure of variability, or total risk. Managers need to target aggressive tracking error with CTEF to maximize the Sharpe and Information Ratios. Similar optimization results are found with the REG10, or GLER, expected returns series. The McKinley Capital Management proprietary model, MQ, produces an interesting set of optimization results. First, the Sharpe Ratio rises with increasing targeted and realized tracking errors with both MVM59 and MVTaR optimization techniques. Second, First, the Information Ratio falls with increasing targeted and realized tracking errors with both MVM59 and MVTaR optimization techniques.

If one seeks to maximize the Geometric Mean and Sharpe Ratio, then a targeted 8 percent TE is warranted. To

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

maximize the IR of the MQ portfolios, then a targeted tracking error of 4 percent is sufficient.

Table 2: Global Optimized Portfolios

Universe: Two I/B/E/S Analysts, Top 7500 Market-Capitalized Stocks
Period: 2002-12-31 to 2018-07-31 (Monthly)

Variable	Optimization Technique	Targeted Tracking Error	Geometric Mean	Information Ratio	Sharpe Ratio	Realized Tracking Error
CTEF	MVTaR	4	12.32	0.47	0.702	5.81
	MVTaR	6	13.52	0.56	0.753	7.03
	MVTaR	8	13.96	0.57	0.777	7.67
	MVM59	4	13.33	0.57	0.688	6.53
	MVM59	6	14.53	0.57	0.684	8.65
	MVM59	8	15.75	0.63	0.701	9.74
GLER	MVTaR	4	9.64	0.01	0.578	4.46
	MVTaR	6	10.98	0.25	0.667	5.60
	MVTaR	8	11.51	0.30	0.704	6.43
	MVM59	4	11.50	0.43	0.630	4.50
	MVM59	6	12.93	0.61	0.676	5.53
	MVM59	8	13.18	0.62	0.678	5.79
MQ	MVTaR	4	15.01	1.27	1.032	4.28
	MVTaR	6	15.11	0.93	1.079	5.96
	MVTaR	8	15.11	0.77	1.127	7.17
	MVM59	4	15.78	1.27	0.979	4.88
	MVM59	6	16.21	1.10	1.019	6.03
	MVM59	8	16.56	1.06	1.069	6.57
	Benchmark		9.58		0.571	

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CTEF	MVTaR	4	12.32	0.47	0.702	5.81
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	MVM59	6	14.53	0.57	0.684	8.65
	MVM59	8	15.75	0.63	0.701	9.74
GLER	MVTaR	4	9.64	0.01	0.578	4.46
	MVTaR	6	10.98	0.25	0.667	5.60
	MVTaR	8	11.51	0.30	0.704	6.43
	MVM59	4	11.50	0.43	0.630	4.50
	MVM59	6	12.93	0.61	0.676	5.53
	MVM59	8	13.18	0.62	0.678	5.79
MQ	MVTaR	4	15.01	1.27	1.032	4.28
	MVTaR	6	15.11	0.93	1.079	5.96
	MVTaR	8	15.11	0.77	1.127	7.17
	MVM59	4	15.78	1.27	0.979	4.88
	MVM59	6	16.21	1.10	1.019	6.03
	MVM59	8	16.56	1.06	1.069	6.57
	Benchmark		9.58		0.571	

ITG transactions costs have been taken out of the portfolio returns reported in Table 2. CTEF, GLER, and MQ produce positive excess returns with both MVM59 and MVTaR portfolio optimization techniques. The financial anomalies of EP, BP, CP, SP, CTEF, and PM are reflected in Table 2 reported results. In the CTEF and MQ optimized portfolios outperform in 70% and 77% of the years, respectively. Financial anomalies, as published in 2003 and 2012-3 continue to outperform, with slightly reduced winning percentages, from 83% in 1993 to 77% in 2018. Is that enough for investors? Should that be enough for investors? The excess returns reported in Table 2, particularly for targeted tracking errors of 6 and 8 percent should satisfy investors who seek to maximize the Geometric Mean and the utility of terminal wealth.

Fama (1991) hypothesized that anomalies could not be effectively tested because of changing asset pricing models and the number of factors in multi-factor models. Barillas and Shanken (2018) addressed the issue of changing risk models and factors. and We have addressed these issues in two previous studies and are currently addressing a third issue. First in Guerard and Mark (2003), we based what BARRA USE models were known at that time; there was no look-ahead bias in risk models. Second, in Guerard and Mark (2018) we used the Boolean signal portfolio construction process in which we buy attractively ranked stocks and sell them when they fell through pre-determined level (buy stocks with CTEF or REG10 scores of at least 85 and higher, where 0 is least preferred and 99 is most preferred and sell at 70, holding in equally-weighted portfolios). The Boolean signal teats re-enforced the mean-variance portfolio results. The mean-variance portfolios, with a specified upper bound on stock weights and positive holdings for long-only portfolios produced very reasonable (possible) weights. We do not believe the Brennan-Lo (2011) footnote that repeats the impossible mean-variance optimized portfolios tales told by Wall Street portfolio managers. The Axioma attribution of the Boolean signal portfolios attributed all Active Returns to stock selection in the CTEF model and the majority of the REG10 model Active Returns were due to Specific Returns, or asset selection. Finally, we test are testing whether it makes a difference as to whether we use a (1) mean-variance tracking error at risk model, stressing systematic risk minimization; (2) a mean—variance model without factors (MVM59), using only total risk; or (3) a mean—variance model using only systematic risk.

Let us update the 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 3. Modern robust statistics minimize a scale measure of residuals insensitive to large residuals, such as the median of the ansolute residuals, see Maronna, Douglas, Yohai, and Salibian-Barrera (2019). The least median squares (LMS) estimator was introduced by Hampel (1975) and Rousseeuw (1984). When we use avery large efficiency measure, such as 99%, large outliers have virtiually 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 uses an 85% efficiency default level as a result of Maronna, Douglas, Yoha (2006). We use 99% because of research conversations with Doug Martin, and the resulting higher portfolio simulation Sharpe Ratios.

The role of historical and forecasted earnings in the non-US 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-US universe. The EP, CTEF, REG8, REG9, and REG10 Mean-Variance portfolios produce statistically significant portfolio Active and Specific Returns. 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.[20] In the Russell 3000 (R3) universe, only the ranked CTEF portfolios produced statistically significant portfolio Active and Specific Returns. The R3 EP, REG8, REG9, and REG10 Mean-Variance portfolios did not produce consistently statistically significant portfolio Active returns and significant Stock Specific Returns for the 1/2003 -11/2018 time period. Only the REG8 and REG9 produced statistically significant stock selection at 6 and 8 % targeted tracking errors, respectively. No U.S. portfolio should be run with a tracking error of less than 6 % if one wants to outperform the market.

[20] 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. [20] 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 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.

Table 3: Mean-Variance Models with Tukey OIF99%
Time Period: 12/2002 -11/2018
Universe: MSCI ex US

Portfolios	Info Ratio	Risk Stock Specific Effect	Risk Stock Specific Effect T-Stat	Risk Factors Effect	Risk Factors Effect T-Stat	Risk Total Effect	Risk Factor Returns: Earnings Yield	Medium-Term Momentum	Size	Value	Volatility
REG8_TE4	0.14	5.48	2.73	1.31	1.72	6.79	0.12	-0.91	0.95	1.21	-0.70
REG8_TE6	0.14	6.94	2.76	0.78	1.71	7.72	0.07	-1.18	1.31	1.82	-1.86
REG8_TE8	0.15	7.96	2.75	0.29	1.73	8.26	-0.04	-0.92	1.40	2.25	-2.77
REG9_TE4	0.32	5.38	2.61	2.35	2.80	7.73	0.37	-0.20	0.84	1.24	-0.49
REG9_TE6	0.18	5.49	2.13	2.60	2.93	8.09	0.36	-0.21	1.20	1.89	-1.62
REG9_TE8	0.12	5.52	1.87	2.57	2.80	8.09	0.31	-0.01	1.31	2.39	-2.36
REG10_TE4	0.21	3.07	1.65	3.93	3.62	7.00	0.46	0.56	0.74	1.12	-0.31
REG10_TE6	0.19	3.03	1.49	5.04	3.66	8.08	0.54	0.90	1.04	1.65	-1.31
REG10_TE8	0.22	2.95	1.37	5.72	3.47	8.67	0.57	1.17	1.03	1.89	-1.64
EP_TE4	0.66	7.32	3.70	1.75	2.34	9.07	0.58	0.91	0.08	-0.44	-0.22
EP_TE6	0.50	8.78	3.68	1.03	2.04	9.81	0.68	0.88	0.07	-0.23	-0.37
EP_TE8	0.46	9.78	3.71	1.31	2.22	11.09	0.64	0.72	0.12	-0.05	-0.49
CTEF_TE4	0.79	5.90	3.35	4.02	3.55	9.92	0.76	0.67	-0.13	1.78	0.30
CTEF_TE6	0.76	6.56	3.33	4.79	3.29	11.34	0.92	0.62	-0.03	2.55	0.44
CTEF_TE8	0.67	6.82	3.26	5.35	3.07	12.17	1.00	0.55	-0.10	3.07	0.61
Universe: Russell 3000											
REG8_TE4	0.02	-0.06	-0.05	-0.11	0.17	-0.17	0.10	-0.19	1.93	0.52	-0.80
REG8_TE6	0.18	1.86	1.66	-0.88	-0.24	0.98	-0.31	-0.28	2.88	0.70	-2.04
REG8_TE8	0.06	1.77	1.36	-1.53	-0.50	0.24	-0.74	-0.41	3.57	0.90	-3.11
REG9_TE4	0.12	0.02	0.05	0.31	0.67	0.33	0.53	-0.02	1.82	0.45	-0.61
REG9_TE6	0.25	1.35	1.14	0.15	0.55	1.50	0.43	-0.15	2.93	0.57	-1.87
REG9_TE8	0.38	3.01	2.04	0.06	0.55	3.07	0.29	-0.21	3.49	0.63	-2.97
REG10_TE4	0.12	-0.17	-0.17	0.52	0.89	0.35	0.71	0.18	1.74	0.49	-0.55
REG10_TE6	-0.01	-0.88	-0.62	0.53	0.68	-0.35	0.67	0.18	2.73	0.75	-1.51
REG10_TE8	0.08	-0.42	-0.14	0.85	0.86	0.43	0.61	0.28	3.33	0.83	-2.38
EP_TE4	-0.11	-1.14	-1.39	0.34	0.63	-0.79	0.68	-0.14	2.10	0.45	-0.75
EP_TE6	-0.20	-1.56	-1.27	0.11	0.24	-1.45	0.55	-0.34	3.61	0.67	-2.15
EP_TE8	-0.41	-3.41	-1.73	-0.46	-0.47	-3.87	0.28	-0.64	4.62	0.96	-3.18
CTEF_TE4	0.42	-0.02	0.20	2.03	2.73	2.02	1.29	0.72	1.96	0.04	-0.63
CTEF_TE6	0.42	0.35	0.57	2.59	2.26	2.95	1.66	1.07	3.20	0.07	-1.63
CTEF_TE8	0.52	1.61	1.36	3.30	2.24	4.92	1.81	1.41	4.07	0.18	-2.89

Another means to analyze the updated non-US and R3 portfolios is to directly compare Information Ratios, IRs, Sharpe Ratios, ShR, and Draw Downs, DD. Draw downs do not vary as much as one might expect from varying targeted tracking errors. In non-US portfolios, the Sharpe Ratios and IRs are maximized at a targeted 6% level with CTEF and 8% with REG9. In the U.S., the maximum TE of 8% maximizes the Sharpe Ratios and Information Ratios.

We have shown how forecasted earnings acceleration produces highly statistically significant stock selection in Non-US and U.S. stock universes. CTEF, REG8, REG9, and REG10 models optimized portfolios produce higher Active and Specific Returns in Non-U.S. stocks, whereas only CTEF consistently produces statistically significant Specific Returns in U.S. The non-US CTEF and REG9 models outperform in 80% of the years, post-publication of 2003. The U.S. CTEF and REG9 models outperform in 60% of the years. Both APT and Axioma optimization systems produced highly statistically significant asset selection.

IX: REAL-TIME RESULTS

In 1993, Bloch et al. (1993) and Guerard, Takano, and Yamane (1993) reported real-time results in footnotes in the per-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 McKinley Capital Management Emerging Growth (EM) strategy had been formulated in 2006, funded in 2011, and had been a top-decile performing strategy in real-time. The EM portfolio has produced over 450 basis points, annualized, of Active Returns (statistically significant, since-inception). Stock selection is positive, 37 basis points, though it has fallen since the initial (2017) publication, and is no longer statistically significant. McKinley Capital 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. [21]

MCM has managed a non-US Growth portfolio for over 23 years. The portfolio has produced over 210 basis points, annualized, of Active Returns (no longer statistically significant, since-inception). Stock selection is positive, 44 basis points annualized, and is no longer statistically significant. McKinley Capital Management (MCM) is a global growth specialist and one would expect positive exposures to growth and medium-term

[21] 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.

momentum. The exposure to growth has lost the portfolio 12 basis points whereas the medium-term momentum exposure produced 194 basis points of factor contribution. The reader immediately sees that the EM portfolio produces more than 150 basis points of medium-term momentum returns than the non-US portfolio.

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 fine 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. The MCM non-US portfolio, with an AUM exceeding $2 billion, is in the top two quintiles for 5-years and in the top half since-inception. The non-US universe benchmark is at the 97th percentile (almost everyone beats the benchmark); whereas the EM benchmark is at the 73th percentile.[22] In U.S. and non-US portfolios, we are finding that all three risk analyses produce similar statistically significant Active Returns and Specific Returns, Sharpe Ratios, and Information Ratios. This is a risk-return trade-off.

5. Summary and Conclusions

We report that an earnings forecasting model continues to produce statistically significant asset selection in global stocks, 2003-11/2018. We report two variations of Markowitz mean-variance optimization, traditional mean-variance and mean-variance tracking error at risk techniques, are particularly efficient for producing efficient frontiers using a forecasted earnings acceleration model, CTEF, and a composite, robust-regression

[22] 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.

based ten-factor model, REG10. Have markets and stock selection models changed since Bloch, Guerard, Markowitz, Todd and Xu (1993) and Guerard and Mark (2003) published their studies? No, CTEF and 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. The authors believe that financial anomalies exist, persist, and most likely will exist.

The authors have shown in Guerard, Gillam, Markowitz, Xu, and Wang (2018) 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. Are markets efficient? No, but significant databases and computers are required to outperform.

Paradigms in Financial Anomalies in the Compustat, CRSP, and I/B/E/S Era

Paradigms in Financial Anomalies in the Compustat, CRSP, and I/B/E/S Era

			Dimson (1988)	Jacobs & Levy (1988) Tested: 1978- 1986	Levy (1999)	Guerard & Markowitz (2018) Tested: 2003-2017		
Author	**Publication Date**	**Primary Variable (S)**	**Anomaly**	**Pure Anomaly**	**Anomaly**	**Pure Anomaly**	**Author**	**Publication**
Jaffe	1974	Insider Trading			Listed	VERIFIED	Jaffe	Special Information and Insider Trading. *Journal of Business* 47, 410-428.
Latane and Jones	1977	SUE			Listed		Latane and Jones	Standardized Unexpected Earnings: A Progress Report. *Journal of Finance* 32, 1457-1465.
Basu	1977	Low P/E		VERIFIED	Listed	VERIFIED	Basu	Investment Performance of Common Stocks in Relations to their Price Earnings Ratios: A Test of Market Efficiency. *Journal of Finance* 32 ,663-682.
Ball	1978	Yield			Listed	VERIFIED	Ball	Anomalies in Relationshps Between Securities' Yields and Yield Surogates. *Journal of Financial Economics* 6, 103-126.
Blume	1980	Yield			Listed	VERIFIED	Blume	Stock Returns and Dividend Yields; Some More Evidence. *Review of Economics and Statistics* 65, 562-577.
Banz	1981	Size	7 CHAPTERS	VERIFIED	Listed		Banz	The Relationship Between Return and the Market Value of Common Stock. *Journal of Financial Economics* 9, 3-18.
Reinganum	1981	Low P/E			Listed	VERIFIED	Reinganum	Misspecification of Capital Asset Prices: Empircal Anomalies based on Earnings Yields and Market Values. *Journal of Financial Economics* 12, 19-46.
Elton, Gruber, and Gultekin	1981	Analysts' Forecasts & Revisions		VERIFIED	Listed	VERIFIED	Elton, Gruber, and Gultekin	Expectations and Share Prices. *Management Science* 27, 975-987.
Rendelman, Jones, and Latane	1982	SUE		VERIFIED	Listed		Rendelman, Jones, and Latane	Empirical Anomalies based on Unexpected Earnings and the Importance of Risk Adjustments. Journal of Financial Economics 12, 19-46.
Tinic and West	1984	CAPM & January	CHAPTER		Listed	VERIFIED	Tinic and West	Risk and Return: January versus the rest of the Year.*Journal of Financial Economics* 13, 561-574.
Rosenberg, Reid, and Lanstein	1985	Value (B/P) and One-Month Reversal				VERIFIED	Rosenberg, Reid, and Lanstein	Persuaive Evidemce of Market Inefficiency. *Journal of Portfolio Management* , 9-16.
Tinic and West	1986	CAPM & January			Listed	VERIFIED	Tinic and West	Risk, Return, and Equilibrium; A Revisit, *Journal of Political Economy* 94, 126-147.
Keim	1986	Size, BP	CHAPTER		Listed		Keim	Stock Market Regularities: A Synthesis of the Evidence and Explanations. In Dimson, Ed., *Stock Market Anomalies.* Cambridge: Cambridge University Press.
Gultekin and Gultekin	1987	High EP			Listed	VERIFIED	Gultekin and Gultekin	Stock Return Anomalies and Tests of the APT. *Journal of Finance* 42, 1213-1224.
Jacobs and Levy	1989	Size			Listed	VERIFIED	Jacobs and Levy	Forecasting the Size Effect.*Financial Analysts Journal* 45, 38-54.
Lakonishok and Vermaelen	1990	Buybacks			Listed	VERIFIED	Lakonishok and Vermaelen	Anomalous Price Behavior Around Repurchase Tender Offers. *Journal of Finance* , 45, 455-477.
Wheeler	1991	Analysts' Forecast Breadth				VERIFIED	Wheeler	Changes in Consesnsus Earnings Estimates and Their Impact ion Stock Returns
Fama and French	1992	Beta, Size, HML			Listed	VERIFIED	Fama and French	Cross-Sectional Variation in Expected Stock Returns." *Journal of Finance 47, 427-465.*
Bloch, Guerard, Markowitz, Todd and Xu	1993	High EP, BP, CP, SP & Relatives			Listed	VERIFIED	Bloch, Guerard, Markowitz, Todd and Xu	A Comparison of Some Aspects of the U.S. and Japanese Equity Markets." *Japan & the World Economy* 5, 3-26.
Lakonishok, Shleifer, and Vishny	1994	High EP, BP, and CP			Listed	VERIFIED	Lakonishok, Shleifer, and Vishny	Contrarian Investment, Extrapolation and Risk. *Journal of Finance* 49, 1541-1578.
Fama and French	1995	Beta, Size, HML, Momentum			Listed	VERIFIED	Fama and French	Size and Book-to-Market Factors in Earnings and Returns. *Journal of Finance 50, 131-155.*

Author	Publication Date	Primary Variable (S)	Anomaly	Pure Anomaly	Anomaly	Pure Anomaly	Author	Publication
Haugen and Baker	1996	High EP, BP, CP & SP			Listed	VERIFIED	Haugen and Baker	Commonality in the Determinants of Expected Stock Returns. *Journal of Financial Economics* 25, 401-439.
Guerard, Gultekin, and Stone	1997	High EP, BP, CP, SP, Relatives, and Analysts' Forecasts, Revisions & Breadth			Listed	VERIFIED	Guerard, Gultekin, and Stone	The Role of Fundamental Data and Analysts' Breadth, Forecasts, and Revisions in the Creation of Efficient Portfolios. in Chen, Editor. *Research in Finance* 15.
Fama and French	1998	Price Momentum			Listed	VERIFIED	Fama and French	Dissecting Anomalies. *Journal of Finance*, 63, 1653-1678.
Lo, Mamaysky,and Wang	2000	Price Momentum				VERIFIED	Lo, Mamaysky,and Wang	Foundations of Technical Analysis, *Journal of Finance* 55, 1705-1765.
Sadka	2006	Price ans Earnings Momentum				VERIFIED	Sadka	Momentum and Post-earnings Annuncement Drift Anomalies: The role of liquidity Risk. *Journal of Financial Economic*s 80, 309-349
Ramnath, Rock, and Shane	2008	Analysts' Forecasts & Revisions			Listed	VERIFIED	Ramnath, Rock, and Shane	The Financial Analyst Forecasting Literature: A Taxonomy with Suggestions for Further Research. *International Journal of Forecasting* 24, 34-75.
Haugen and Baker	2010	High EP, BP, CP, SP & Relatives			Listed	VERIFIED	Haugen and Baker	Case Closed. In J.B. Guerard, Jr., Editor, *The Handbook of Portfolio Construction: Contemporary Applications of Markowitz Techniques.New York:* Springer.
Stone and Guerard	2010	High EP, BP, CP, SP, and Relatives				VERIFIED	Stone and Guerard	Methodologies for Isolating and Assessing the Portfolio Performance Potential of Stock Return Forecast Models with an Illustration, in J.B. Guerard, Jr., Editor,
Guerard, Markowitz, and Xu	2013	High EP, BP, CP, SP, Relatives, Momentum and Analysts' Forecasts, Revisions & Breadth				VERIFIED	Guerard, Markowitz, and Xu	Efficient Global Portfolios: Big Data and Investment Universes. *IBM Journal of Research and Development* 57, 11:1 – 11.11.
Guerard, Markowitz, and Xu	2014	High EP, BP, CP, SP, Relatives, Momentum and Analysts' Forecasts, Revisions & Breadth				VERIFIED	Guerard, Markowitz, and Xu	The Role of Effective Corporate Decisions in the Creation of Efficient Portfolios. *IBM Journal of Research and Development,* 58, No. 6, Paper 11.
Guerard, Markowitz, and Xu	2015	High EP, BP, CP, SP, Relatives, Momentum and Analysts' Forecasts, Revisions & Breadth				VERIFIED	Guerard, Markowitz, and Xu	Earnings Forecasting in a Global Stock Selection Model and Efficient Portfolio Construction and Management. *International Journal of Forecasting* 31, 550-560.
Fu and Huang	2016	Buybacks				VERIFIED	Fu and Huang	The Persistence of Long-Run Abnormal Returns Following Stock Repurchases and Offerings, *Management Science* 62, 964-984.
Harvey, Liu, and Zhu	2016	A Review of 350 Papers					Harvey, Liu, and Zhu	and the Cross-Section of Expected Returns. Review of Financial Studies 29, 5-68.

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B. Jacobs and K. Levy, "Disentangling Equity Return Regularities: New Insights and Investment Opportunities",. *Financial Analysts Journal* 44 (1988), 18-48.

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McKinley Capital Management, LLC DISCLOSURE

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:

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

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

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

or

$$\sum \psi\,(x_i;\ T_n) = 0 \quad \text{(A-3)}$$

where

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

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

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

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

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

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

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

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

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

where

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

An alternative to the Huber weighting function is the Beaton-tweeny (1974) bisquare function where σ is solved from:

$$\frac{1}{n-p} \sum X_d \left(\frac{r_i}{\sigma}\right) \ = \beta \qquad \text{(A-210)}$$

with

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

If $|x| < \ d$ otherwise β $=$ f$X_d \, d\phi(s)$

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:

$$w_i = \begin{cases} (1 - (\frac{|e_i|}{\sigma_\varepsilon} / 4.685^2)^2, & if \ \frac{|e_i|}{\sigma_\varepsilon} \geq \ 4.685, \\ 0, & if \ \frac{|e_i|}{\sigma_\varepsilon} < 4.685. \end{cases} \qquad \text{(A-11)}$$