Received: 13 November 2018 | Accepted: 13 November 2018
DOI: 10.1002/cfp2.1022

WILEY

ORIGINAL ARTICLE

The existence and persistence of financial anomalies: What have you done for me lately?

John Guerard[1] | Harry Markowitz[2]

[1]Quantitative Research, McKinley Capital Management, LLC, Anchorage, Alaska

[2]Harry Markowitz & Company, San Diego, California

Correspondence
John Guerard, Quantitative Research, McKinley Capital Management, LLC, Anchorage, AK 99503.
Email: jguerard@mckinleycapital.com

The purpose of this study is to document the existence, persistence, and effectiveness of publicly available variables linked to financial anomalies during the 1979–1999 time period with particular emphasis on earnings forecasts. It then tests whether these variables have held up through the 2003–2017 time period. We report three results: (a) many of the reported financial anomalies published in the 1979–1999 time period maintain their statistically significant active (or excess) returns; (b) the anomalies are larger in non-U.S. markets than in the U.S.; and (c) reasonable transactions costs do not destroy the excess returns.

KEYWORDS
behavioral finance, investments, portfolio choice

1 | INTRODUCTION

Financial anomalies and regularities in returns have been studied for over 80 years in the United States. If these patterns are both persistent and observable, investors should incorporate this information into their decision-making, financial plans, and portfolio construction. The importance of taking account of return regularities in portfolios and plans arises because these patterns may reflect premia serving as 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.

We find that measures related to historic earnings are highly statistically significantly associated with stock returns both prior to the time when they were first published in the academic literature and after. Earnings forecasting data in particular have been consistent and highly statistically significant sources of excess returns. If one started a career on Wall Street or became a financial planner during the period 1987–1991, one could have known an extensive and growing body of knowledge on historic and forecasted earnings per share modeling and ostensibly utilized this knowledge thereafter. The reported excess returns of the 1980s continued to be recognized and tested through the 1990s and were apparent in returns after the period. See Chart 1 for the behavior of the S&P 500 Index from January 1986 - October 24, 2018

Specifically, we test a set of U.S. and global variables over the past 16 years 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 quantitative-based models, built on anomalies known at the time, have outperformed indexes in over 70% of the years. Whether these return patterns reflect reward for bearing risk or whether they are reliable sources of true alpha, they have persisted out of sample and, as such, are necessarily important for investors of all varieties.

The remainder of the paper contains four sections. The first section addresses what we knew between 1987 and 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. This section also provides an overview of the fundamental variables used in our composite models. The second section discusses the fundamental variables, the earnings forecasting models and the price momentum variables used in our

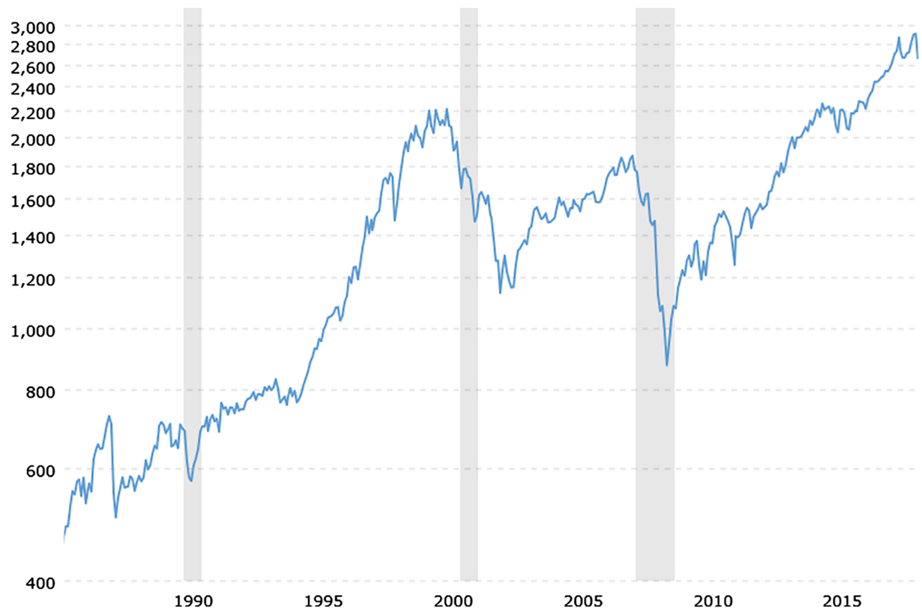

CHART 1 S&P performance from January 1 of 1986 at 208.20 to October 24 2018 at 2656.16

expanded composite models. The third section examines risk models used in the analysis of the post-Global Financial Crisis time period. The fourth section discusses the existence and persistence of financial anomalies between 2003 and 2017. The fifth section presents conclusions and thoughts regarding future research.

2 | WHAT WE KNEW IN 1991: TESTS OF FUNDAMENTAL DATA

What did we know in 1991? Students had been taught since the 1930s that fundamental data, earnings, cash flow, book value, net current asset value, and sales drove stock returns. Graham and Dodd (1934), Williams (1938), Graham, Dodd, and Cottle (1962), Loeb (1971), Elton and Gruber (1972), Graham (1973), and Dremen (1979) were books intelligent investors read. The books supported the "low price-earnings (P/Es)" 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), and Levy (1999). 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, Hamao, and Lakonishok (1991), Bloch, Guerard Jr., Markowitz, Todd, and Xu (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.

$$\begin{aligned} \mathrm{TR} = {} & w_0 + w_1\mathrm{EP} + w_2\mathrm{BP} + w_3\mathrm{CP} + w_4\mathrm{SP} + w_5\mathrm{REP} \\ & + w_6\mathrm{RBP} + w_7\mathrm{RCP} + w_8\mathrm{RSP} + e_t \end{aligned} \tag{1}$$

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 5 years];

RBP = [current BP ratio]/[average BP ratio over the past 5 years];

RCP = [current CP ratio]/[average CP ratio over the past 5 years]; and

RSP = [current SP ratio]/[average SP ratio over the past 5 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. Bloch et al. (1993) tested the relative explanatory and predictive merits of alternative regression estimation procedures. They reported several results: (a) The robust regression-constructed eight-factor composite model portfolio produced higher Sharpe ratios and geometric means than the ordinary least squares (OLS)-constructed composite model portfolio; (b) survivor bias was not statistically significant; and (c) tighter turnover led to higher portfolio returns for their tested strategies.

3 | WHAT WE KNEW IN 2002 AND 2012: TESTS OF FUNDAMENTAL, EXPECTATIONS, AND PRICE MOMENTUM DATA

Bruce and Epstein (1994)[1] provide a summary of key studies of the effectiveness of corporate earnings forecasting variables. Further, Brown (1999) contains over 500 abstracts of studies using Institutional Broker Estimation Services (I/B/E/S) data.[2] By 1999, 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 significantly correlates of stock returns. For example, Guerard Jr. and Mark (2003) demonstrate that CTEF, and a nine-factor model of REG8 plus CTEF is also highly (statistically) significantly correlated with subsequent stock returns.

Financial economists have empirically examined the determinants of stock 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 nonrandom 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), Jagadeesh and Titman (1993), Conrad and Kaul (1991, 1993, 1998), Lo, Mamaysky, and Wang (2000), and Lo (2017) formalizes and extends the technical analysis and price momentum literature. 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.[3] Jagadeesh and Titman (1993) construct portfolios based on 6 months of positive price momentum, hold the portfolios for 6 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, the global electronic marketplace for buying and selling securities, as well as the benchmark index for U.S. stocks—demonstrating price momentum and technical analysis variables enhanced portfolio returns over the long-run.

Expanding on the work of Fama and French (1992, 1995, 2018) and Guerard Jr. and Mark (2003), Guerard Jr, Xu, and Gultekin (2012) create a 10-factor stock selection model for the U.S. expected returns that includes price momentum—the USER model.[4] Guerard Jr, Rachev, and Shao (2013) and Guerard Jr. and Mark (2003) apply a 10-factor model to global stocks, referring to the model as GLER (GLobal Equity Return), or REG10 (see Equation 2).

$$\mathrm{TR}_{t+1} = a_0 + a_1\mathrm{EP}_t + a_2\,\mathrm{BP}_t + a_3\mathrm{CP}_t + a_4\mathrm{SP}_t + a_5\mathrm{REP}_t + a_6\mathrm{RBP}_t + a_7\mathrm{RCP}_t + a_8\mathrm{RSP}_t + a_9\mathrm{CTEF}_t + a_{10}\mathrm{PM}_t + e_t, \quad (2)$$

where:

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

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

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

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

REP = [current EP ratio]/[average EP ratio over the past 5 years];

RBP = [current BP ratio]/[average BP ratio over the past 5 years];

RCP = [current CP ratio]/[average CP ratio over the past 5 years];

RSP = [current SP ratio]/[average SP ratio over the past 5 years];

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

PM = price momentum; and

e = randomly distributed error term.

The 10-factor model was developed and tested in U.S. markets by Guerard Jr et al. (2012) and Guerard Jr, Markowitz, and Xu (2014), and in global markets by Guerard Jr. et al. (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.[5] In addition, the earnings forecasting model, CTEF, continues 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 Jr. and Mark (2018).

4 | MARKOWITZ RISK MODELING AND AXIOMA RISK MODELS: 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 weights multiplied by their respective expected returns. The portfolio *SD* is the sum of the weighted covariances.

$$E(R_p) = \sum_{i=1}^{N} x_i E(R_i) = \sum_{i=1}^{N} x_i \mu_i \tag{3}$$

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j c_{ij} \tag{4}$$

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

The efficient frontier can be traced out by

$$minimize_{\{x_i \geq 0, x_i \leq \bar{u}\}} \; x^T C x - \lambda \mu^T x \tag{5}$$

where λ is the risk–return trade-off parameter and $\bar{u}$ 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:

$$R_j = \sum_{k=1}^{K} \beta_{jk} \tilde{f}_k + \tilde{e}_j. \tag{6}$$

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.[6] 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.

$$C = \beta C_{f,f} \beta' + \Sigma. \tag{7}$$

If an investor is more concerned about tracking a particular benchmark, the mean–variance (MV) optimization in Equation (7) can be reformulated as a MV tracking error (TE) at risk (MVTaR) optimization:

$$minimize \; (x - x_b)^T C (x - x_b) - \lambda \mu^T (x - x_b) \tag{8}$$

where x_b is the weight vector of the benchmark. We will follow this approach below.

Barr Rosenberg and others in 1975 introduced the BARRA US Equity Model, often denoted USE1.[7] Within the USE1 model, raw data are normalized by subtracting a mean and dividing through by the variable *SD*; 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 *SD* 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.[8] The domestic BARRA E3 (USE3, or sometimes denoted US-E3) model has 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. BARRA is a now proprietary model; that is, the composite model weights are not disclosed.

In the 1980s, a commercially available statistical risk model, Advanced Portfolio Technologies (APT), was developed by John Blin and Steven Bender and was documented in Blin et al. (1997) and Guerard Jr et al. (2013). Another commercially available risk model is the Axioma Risk Model.[9] The Axioma Robust Risk Model is a multi-factor risk model, in the tradition of the Barra model. Axioma offers both United States 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 OLS 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.

Axioma has pioneered two techniques for effective portfolio construction. The first technique, known as the Alpha Alignment Factor (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 underestimation 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:

$$C_{\text{new}} = C + \sigma_{\underline{\alpha}}^2 \underline{\alpha} \cdot \underline{\alpha}' + \sigma_{\underline{\gamma}}^2 \underline{\gamma} \cdot \underline{\gamma}', \tag{9}$$

where α is the 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, that is, the orthogonal component, with risk model factors. Saxena and Stubbs (2012) applied the AAF to the USER model 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, which not only improves the accuracy of risk prediction, but also 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. Pushing out the efficient frontier maximizes the geometric mean, see Markowitz (1952, 1959, 1976, 1987, 2013) and Latane, Tuttle, and Jones (1975).

Guerard Jr. et al. (2015) tested the Axioma risk models. Guerard Jr. et al. (2015) tested CTEF and a 10-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; demonstrating a realized risk-return trade-off. Guerard Jr. et al. (2015) also reported that statistically based risk models using principal components, the Sungard APT and Axioma, produced more efficient trade-off curves than Axioma the fundamental risk model. 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. Saxena and Stubbs (2012) report positive frontier spreads. Guerard Jr and Chettiappan (2017) and Guerard (2013) also report the effectiveness of AAF modeling in an emerging markets portfolio.

The second technique, known as the Custom Risk Model, 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 (FAP) that is due to constraints.[10]

5 | 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 period, 2003–2018.

Guerard Jr. et al. (2015) reported three levels of testing investment strategies, see Farrell (1997) and Guerard (2017) for textbook treatments. 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 transaction 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's (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 Jr et al. (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). How often should portfolios turnover? Bloch et al. (1993) argue for lower turnover to maximize the GM. Guerard Jr. and Mark (2018) agree, reporting that monthly turnover of 10% maximizes the GM. TO (10) means 5% buys and 5% sells (or both way, round-trip turnover). Turnover exceeding 10% buys with signals defined by the CTEF variables are ruinous. Guerard Jr. 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 —MV CTEF and REG10 portfolios produced ~300–350 basis points of specific returns for the 20-year time periods, 1996–2016 time period. In the U.S. portfolios, equally weighted 125 stock portfolios outperform MV 4% portfolios.[11] In a summary, Axioma attribution analysis of these U.S. portfolios reports that only the ranked CTEF variable produces statistically significant portfolio active total returns and stock specific returns in the United States. The CTEF, and REG10 portfolios produced statistically significant portfolio active total returns but insignificant stock specific returns in U.S. stocks for the January 2003–November 2016 time period.

In the Morgan Stanley Capital International (MSCI) non-U.S. and Europe, Australia, and Far East (EAFE) universes, Guerard Jr. and Mark (2018) reported that the CTEF ICs were higher than the REG10 or GLER ICs in their 10, 5, 3, and 1-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. 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% level. Guerard Jr. and Mark (2018) reported that only ranked CTEF is statistically significant in the United States, whereas globally, ranked CTEF and REG10 are statistically significant in total active returns and risk stock selection returns.

In this section, we report results for the top 7,500 largest market-capitalized global stocks with at least two analysts' forecasts, January 2003–June 2018. Our simulation conditions assume 8% monthly turnover, 35 basis point threshold positions, an upper bound in MV optimization of 4% on security weights, and the Investment Technology Group (ITG) transactions costs.[12] We use two MV optimization techniques. First, the traditional MV 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 MVTaR where 20 orthogonal (principal components analysis) betas are estimated. Our portfolio looks almost exactly like the market index benchmark, the MSCI All

TABLE 1 Global optimized portfolios

Universe: Two I/B/E/S analysts, top 7,500 market-capitalized stocks						
Period: December 31, 2002 to July 31, 2018 (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	

Country World index, on 20 dimensions. MVTaR maximizes returns while minimizing the underperformance of an index portfolio return. The optimization uses the ITG transactions costs curves discussed in Borkovec, Domowitz, Kiernan, and Serbin (2010). The start date on 2003 is determined by ITG transactions costs data coverage. The McKinley capital models were in place in 2006, see McKinley Capital (2006). We use the Axioma global statistical risk model, version 4.

In Table 1, we show that with the CTEF variable, The MVM59, the traditional Markowitz (1959) MV optimization analysis outperforms the MSCI All Country Word benchmark. The IR, the ratio of portfolio active (excess) return relative to the portfolio TE is maximized with a targeted TE of 8%, producing active returns exceeding 6% and an IR of 0.63. The MVTaR portfolio substantially reduces risk and TE. The MVTaR CTEF TE of 8% maximizes the ShR, the ratio of portfolio active return relative to its *SD*, its measure of variability, or total risk. Managers need to target aggressive TE with CTEF to maximize the ShR and IR. 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 ShR rises with increasing targeted and realized TEs with both MVM59 and MVTaR optimization techniques. Second, the IR falls with increasing targeted and realized TEs with both MVM59 and MVTaR optimization techniques. If one seeks to maximize the GM and ShR, then a targeted 8% TE is warranted. To maximize the IR of the MQ portfolios, a targeted TE of 4% is sufficient.

The financial anomalies of EP, BP, CP, SP, CTEF, and PM are presented in Table 1. In the CTEF and MQ optimized portfolios outperform in 70% and 77% of the years, respectively. Financial anomalies, as published in 2003 and 2012–2013 continue to outperform. Guerard Jr., 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). See Brealey et al. (2006), Elton, Gruber, Brown, and Goetzman (2007), Haugen and Baker (2010), and Levy (2012) for more recent anomalies surveys.

Fama (1991) claimed that anomalies may be correctly identified due to changing risk models and their underlying factor structures. We agree, and address this issue with two approaches. First, the MVM59 optimizations use variance as risk and a full covariance estimation. No factors are involved and changing risk factors are not an issue. Second, the authors use a Boolean signal for stock selection in Guerard Jr. et al. (2015). In this test, one buys a stock with a CTEF score that exceeds 85 and sells the stock when the CTEF score falls below 70. Stocks are held in an equally weighted portfolio. Such a model does not use optimization at all and is a great first-round test of an anomaly. One then uses an Axioma fundamental risk model, version 4, to perform access sock selection. One finds for the CTEF variable that the Boolean signal produces an active return of 10.33% annualized ($t = 5.97$, highly statistically significant), for the January 2003–August 2018 time period. Moreover, the CTEF Boolean signal test produced 608 basis points ($t = 10.24$) of specific returns. Factor contributions are

308 basis points, led by medium-term momentum factor contributions of 148 basis points ($t = 8.06$). The authors recently used the Boolean signal argument to address a footnote in Brennan and Lo (2011), which repeated several Wall Street "researchers" claiming that Markowitz MV analysis can produce impossible frontiers. We do not find such results with a reasonably specified upper stock bound and reasonable turnover constraints.

6 | 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 returns 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 Jr. and Mark (2003) and Guerard Jr et al. (2013) published their studies? No, CTEF and REG10 still dominate most other models, including the 36 models tested in Guerard Jr. et al. (2018), including the post-Global Financial Crisis.

Guerard Jr. 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 5-year and since-inception active returns and positive specific returns; they are little more than malarkey. Malkiel (1973, 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. Moreover, the recent findings of Gillam, Guerard Jr., 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, see Kuhn & Johnson (2013), new data sources and modeling techniques, offer the potential for investor risk-adjusted return enhancement. Many Wall Street practitioners, such as Subramanian, Suzuki, Makedon, and Carey (2013), test 700 or more variables. We report that no more than 5-12 variables are statistically significant. Evidence suggests that about two in 20 new databases enhancement the financial anomalies we report. Thus, we see the possibility for about 15–20% 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.

ACKNOWLEDGEMENTS

We thank Bijan Beheshti of FactSet for assistance with certain attribution analysis reported in the paper. We thank co-editors, Vicki Bogan and Chris Geczy, for comments and suggestions. The authors appreciate the editorial assistance of Allison Capps. The views and opinions expressed in this paper are those of the authors and may not represent or reflect those of McKinley Capital Management, LLC. All information contained herein is believed to be acquired from reliable sources, but accuracy cannot be guaranteed. This paper is for informational purposes only, was prepared for academics and financially sophisticated and institutional audiences and does not represent specific financial services or investment recommendations or advice.

ENDNOTES

[1]The Bruce and Epstein (1994) and Brown (1999) works contain much of the rich history of earnings forecasting and resulting excess returns. Bruce and Epstein included the work of researchers such as Elton, Gruber, and Gultekin (1981), who developed I/B/E/S database and published the initial research (1981 and 1984). Hawkins, Chamberlain, and Daniel (1984) developed tests for analyst revisions, and Guerard and Stone (1992), which tested time series model forecasts versus analysts' forecasts. The Elton et al. (1981) paper is one most influential analyses in earnings forecasting and security analysis. Wheeler (1994) 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 in 1994. Guerard (1997) and Guerard Jr, Gultekin, and Stone (1997) created a composite forecasting variable consisting of consensus analysts' forecasts, forecast revisions, and the breadth variables. This result complements that of Lakonishok, Shleifer, and Vishny (1994) in showing that rank-ordered portfolio returns have significant value and growth components. Guerard and Stone (1992), Guerard Jr et al. (1997), Hong, Kubik, and Solomon (2000), Hong and Kubik (2003), and Guerard Jr., Markowitz, and Xu (2015) are among the thousands of studies of analysts' forecasting efficiency and how analysts' forecasts enhance portfolio returns.

[2]Analysts' forecasts of earnings per share (eps), eps revision, and the direction of eps forecast revisions were incorporated into the 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.

[3]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.

[4]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.

[5]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.

[6]The estimation of factors, or betas, can be accomplished using firm fundamental data, as in Rosenberg (1974), Rosenberg and Marathe (1975, 1976), Ross (1976), Ross and Roll, (1980), Rosenberg and Marathe (1979), and Menchero, Morozov, and Shepard (2010), or principal component analysis of historical stock returns, as in Blin, Bender, and Guerard Jr (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), Conner and Korajczyk (2010), Stone and Guerard (2010), and Connor, Goldberg, and Korajczyk (2010).

[7]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) and Rudd and Rosenberg (1979). Rudd and Clasing (1982) is an excellent reference for how the BARRA equity model is constructed.

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

[9]*Axioma Robust Risk Model Handbook*, January 2010.

[10]Saxena and Stubbs (2012) define the FAP, which arises as a result of the complex interactions between the factors used for forecasting expected returns, risks, and constraints. 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.

[11]Levy and Duchin (2010) argued that if the ex ante parameter 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.

[12]ITG estimates our transactions costs to be about 60 basis points, each way, for 2011–2015.

REFERENCES

Basu, S. (1977). Investment performance of common stocks in relations to their price earnings ratios: A test of market efficiency. *Journal of Finance*, *32*, 663–682.

Blin, J. M., Bender, S., & Guerard, J. B., Jr. (1997). Earnings forecasts, revisions and momentum in the estimation of efficient market-neutral Japanese and U.S. portfolios. *Research in Finance*, *15*, 93–114.

Bloch, M., Guerard, J. B., Jr., Markowitz, H. M., Todd, P., & Xu, G.-L. (1993). A comparison of some aspects of the U.S. and Japanese equity markets. *Japan and the World Economy*, *5*, 3–26.

Borkovec, M., Domowitz, I., Kiernan, B., & Serbin, V. (2010). Portfolio optimization and the cost of trading. *Journal of Investing*, *19*, 63–76.

Brealey, R. A., Myers, S. C., & Allen, F. (2006). *Principles of corporate finance* (8th ed.). New York, NY: McGraw-Hill/Irwin.

Brennan, T. J., & Lo, A. (2011). Impossible frontiers. *Management Science*, *56*, 905–923.

Brown, L.D. 1999. *Annotated I/B/E/S bibliography.*

Bruce, B., & Epstein, C. B. (1994). *The handbook of corporate earnings analysis*. Chicago, IL: Probus Publishing Company.

Brush. J. (2001). Price momentum: A twenty-year research effort. *Columbine Newsletter.*

Chan, L. K. C., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and stock returns in Japan. *Journal of Finance*, *46*, 1739–1764.

Chu, Y , Hirshleifer, D. & Ma, L. (2017). *The casual effect of limits on arbitrage on asset pricing models.* (NBER Working Paper 24144). Retrieved from http://www.nber.org/papers/w24144

Conner, G., & Korajczyk, R. A. (2010). Factor models in portfolio and asset pricing theory. In J. Guerard (Ed.), *The handbook of portfolio construction: Contemporary applications of Markowitz techniques*. New York, NY: Springer.

Connor, G., Goldberg, L., & Korajczyk, R. A. (2010). *Portfolio risk analysis*. Princeton, NJ: Princeton University Press.

Conrad, J., & Kaul, G. (1989). Mean reversion in short-horizon expected returns. *Review of Financial Studies*, *2*, 225–240.

Conrad, J., & Kaul, G. (1991). Components of short-horizon individual security returns. *Journal of Financial Economics*, *29*, 365–384.

Conrad, J., & Kaul, G. (1993). Long-term market overreaction or biases in compound returns. *Journal of Finance*, *59*, 39–63.

Conrad, J., & Kaul, G. (1998). An anatomy of trading strategies. *Review of Financial Studies*, *11*, 489–519.

Cootner, P. (1964). *The random character of stock market prices*. Cambridge, MA: MIT Press.

Deng, S., & Min, X. (2013). Applied optimization in global efficient portfolio construction using earnings forecasts. *Journal of Investing*, *22*, 104–114.

Dimson, E. (1988). *Stock market anomalies*. Cambridge, MA: Cambridge University Press.

Dremen, D. (1979). *Contrarian investment strategy*. New York, NY: Random House.

Elton, E. J., & Gruber, M. J. (1972). *Security analysis and portfolio analysis*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Elton, E. J., Gruber, M. J., Brown, S. J., & Goetzman, W. N. (2007). *Modern portfolio theory and investment analysis* (Seventh ed.). New York, NY: Wiley.

Elton, E. J., Gruber, M. J., & Gultekin, M. (1981). Expectations and share prices. *Management Science*, *27*, 975–987.

Fama, E. F. (1991). Efficient capital markets II. *Journal of Finance*, *46*, 1575–1617.

Fama, E. F., & French, K. R. (1992). Cross-sectional variation in expected stock returns. *Journal of Finance*, *47*, 427–465.

Fama, E. F., & French, K. R. (1995). Size and the book-to-market factors in earnings and returns. *Journal of Finance*, *50*, 131–155.

Farrell, I. L., Ir. (1997). *Portfolio management: Theory and applications*. New York, NY: McGraw-Hill/Irwin.

Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *Journal of Finance*, *63*, 1653–1678.

Fu, F., & Huang, S. (2016). The persistence of long-run abnormal following stock repurchases and issues. *Management Science*, *62*, 964–984.

Gillam, R. A., Guerard, J. B., Jr., & Cahan, R. (2015). News volume information: Beyond earnings forecasting in a global stock selection model. *International Journal of Forecasting*, *31*, 575–581.

Graham, B. (1973). *The intelligent investor*. New York, NY: Harper & Row.

Graham, B., & Dodd, D. (1934). *Security analysis: Principles and technique* (1st ed.). New York, NY: McGraw-Hill Book Company.

Graham, B., Dodd, D., & Cottle, S. (1962). *Security analysis: Principles and technique* (4th ed.). New York, NY: McGraw-Hill Book Company.

Grinold, R., & Kahn, R. (1999). *Active portfolio management*. New York, NY: McGraw-Hill/Irwin.

Guerard, J. B. (1997). Is there a cost to be socially responsible in investing? *Journal of Forecasting*, *16*, 475–490.

Guerard, B., Jr. (2013). *Introduction to financial forecasting in investment analysis*. New York, NY: Springer.

Guerard, J. B., Jr. (2017). *Portfolio construction, measurement, and efficiency: Essays in honor of Jack Treynor*. New York, NY: Springer.

Guerard, J. B., Jr., & Chettiappan, S. (2017). Active quant: Applied investment research in emerging markets. *Journal of Investing*, *26*, 127–137.

Guerard, J. B., Jr., & Mark, A. (2003). The optimization of efficient portfolios: The case for an R&D quadratic term. *Research in Finance*, *20*, 213–247.

Guerard, J. B., Jr., & Mark, A. (2018). Earnings forecasts and revisions, price momentum, and fundamental data: Further explorations of financial anomalies. In C. F. Lee (Ed.), *Handbook of Financial Econometrics*. Singapore: World Scientific (forthcoming).

Guerard, J. B., Jr., & Stone, B. K. (1992). Composite forecasting of annual corporate earnings. *Research in Finance*, *10*, 205–230.

Guerard, J. B., Jr, Gillam, R.A., Markowitz, H. Xu, G., Deng, S. & Wang, E. (2018). Data mining corrections testing in Chinese stocks. *Interfaces 48*, 108-120.

Guerard, J. B., Jr., Gultekin, M., & Stone, B. K. (1997). The role of fundamental data and analysts' earnings breadth, forecasts, and revisions in the creation of efficient portfolios. *Research in Finance*, *15*, 69–92.

Guerard, J. B., Jr., Markowitz, H. M., & Xu, G. (2014). The role of effective corporate decisions in the creation of efficient portfolios. *IBM Journal of Research and Development*, *58*(4), 6.1–6.11.

Guerard, J. B., Jr., Rachev, R. T., & Shao, B. (2013). Efficient global portfolios: Big data and investment universes. *IBM Journal of Research and Development*, *57*(5), 11.1–11.10.

Guerard, J. B., Jr., Xu, G., & Gultekin, M. N. (2012). Investing with momentum: The past, present, and future. *Journal of Investing*, *21*, 68–80.

Guerard, J. B., Jr., & Mark, A. (2003). The optimization of efficient portfolios: The case for an R&D quadratic term. *Research in Finance*, *20*, 213–247.

Guerard, J. B., Jr., Markowitz, H. M., & Xu, G. (2015). Earnings forecasting in a global stock selection model and efficient portfolio construction and management. *International Journal of Forecasting*, *31*, 550–560.

Guerard, J. B., Jr., Markowitz, H. M., Xu, G., & Wang, E. (2018). Global portfolio construction with emphasis on conflicting corporate strategies to maximize stockholder wealth. *Annals of Operations Research*, *267*, 203–219.

Haugen, R., & Baker, N. (2010). Case closed). In J. B. Guerard (Ed.), *The handbook of portfolio construction: Contemporary applications of Markowitz techniques*. New York, NY: Springer.

Haugen, R. A., & Baker, N. (1996). Communality in the determinants of expected results. *Journal of Financial Economics*, *41*, 401–440.

Hawkins, E. H., Chamberlain, S. C., & Daniel, W. E. (1984). Earnings expectations and security prices. *Financial Analysts Journal*, *40*(5), 24–38.

Hong, H., & Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance*, *58*(1), 313–351.

Hong, H., Kubik, J. D., & Solomon, A. (2000). Security analysts' career concerns and the herding of earnings forecasts. *RAND Journal of Economics*, *31*, 121–144.

Jacobs, B. I., & Levy, K. (1988). Disentangling equity return regularities: New insights and investment opportunities. *Financial Analysts Journal*, *44*, 18–43.

Jagadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *48*, 65–91.

Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling*. New York, NY: Springer.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation and risk. *Journal of Finance*, *49*, 1541–1578.

Latane, H., Tuttle, D., & Jones, C. P. (1975). *Security analysis and portfolio management*. New York, NY: The Ronald Press.

Levy, H. (1999). *Introduction to investments* (2nd ed.). Cincinnati, OH: South-Western College Publishing.

Levy, H., & Duchin, R. (2010). Markowitz's mean-variance rule and the Talmudic diversification recommendation. In J. B. Guerard (Ed.), *The handbook of portfolio construction: Contemporary applications of Markowitz techniques*. New York, NY: Springer.

Levy, M. (2012). *The capital asset pricing model in the 21st century*. Cambridge, MA: Cambridge University Press.

Lo, A. (2017). *Adaptive markets*. Princeton, NJ: Princeton University Press.

Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance*, *60*(2000), 1705–1764.

Loeb, G. M. (1971). *The battle for stock market profits*. New York, NY: W.W. Norton & Co.

Malkiel, B. (1973). *A random walk down Wall Street*. New York, NY: W.W. Norton & Company.

Malkiel, B. G. (2003). The efficient markets hypothesis and its critics. *Journal of Economic Perspectives*, *17*, 59–82.

Markowitz, H. (1987). *Mean-variance analysis in portfolio choice and capital markets*. London, England: Basil Blackwell.

Markowitz, H. M. (1952). Portfolio selection. *Journal of Finance*, *7*, 77–91.

Markowitz, H. M. (1959). *Portfolio selection: Efficient diversification of investment* (Cowles Foundation Monograph No. 16). New York, NY: John Wiley & Sons.

Markowitz, H. M. (1976). Investment in the long run: New evidence for an old rule. *Journal of Finance*, *31*, 1273–1286.

Markowitz, H. M. (2013). *Risk-return analysis*. New York, NY: McGraw-Hill.

Markowitz, H. M., & Xu, G. L. (1994). Data mining corrections. *Journal of Portfolio Management*, *21*, 60–69.

McKinley Capital Management, Inc. (2006, June). *An assessment of a McKinley capital emerging markets growth portfolio: A review of factors, returns, and implementation.*

Menchero, J., Morozov, A., & Shepard, P. (2010). Global equity modeling. In J. B. Guerard (Ed.), *The handbook of portfolio construction: Contemporary applications of Markowitz techniques*. New York, NY: Springer.

Nerlove, M. (1968). Factors affecting differences among rates of return in individual common stocks. *Review of Economics and Statistics*, *50*, 312–331.

Rosenberg, B. (1974). Extra-market components of covariance in security returns. *Journal of Financial and Quantitative Analysis*, *9*, 263–274.

Rosenberg, B., & Marathe, V. (1975). The prediction of investment risk: Systematic and residual risk. In *Proceedings of the Seminar on the Analysis of Security Prices* (pp. 85–225). Chicago, IL: University of Chicago.

Rosenberg, B., & Marathe, V. (1976). Common factors in security returns: Microeconomic determinants and macroeconomic correlates. In *Proceedings of the Seminar on the Analysis of Security Prices* (pp. 61–115). Chicago, IL: University of Chicago.

Rosenberg, B., & Marathe, V. (1979). Tests of capital asset pricing hypotheses. In H. Levy (Ed.), *Research in finance* (Vol. 1, pp. 115–223). Greenwich, CT: JAI Press, Inc.

Rosenberg, B., & McKibben, W. (1973). The reduction of systematic and specific risk in common stocks. *Journal of Financial and Quantitative Analysis*, *8*, 317–333.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, *13*, 341–360.

Ross, S. A., & Roll, R. (1980). An empirical investigation of the arbitrage pricing theory. *Journal of Finance*, *35*(2), 1071–1103.

Rudd, A., & Clasing, H. K. (1982). *Modern portfolio theory: The principles of investment management*. Homewood, IL: Dow-Jones Irwin.

Rudd, A., & Rosenberg, B. (1979). Realistic portfolio optimization. In E. Elton & M. J. Gruber (Eds.), *Portfolio theory: 25 years after*. Amsterdam, The Netherlands: North-Holland Publishing Company.

Saxena, A., & Stubbs, R. A. (2012). An empirical case study of factor alignment using the USER model. *Journal of Investing*, *21*, 25–44.

Stone, B. K., & Guerard, J. B., Jr. (2010). Methodologies for isolating and assessing the portfolio performance potential of stock market return forecast models with an illustration. In J. B. Guerard (Ed.), *The handbook of portfolio construction: Contemporary applications of Markowitz techniques*. New York, NY: Springer.

Subramanian, S., Suzuki, D., Makedon, A., & Carey, J. (2013, March). A PM's guide to stock picking. Bank of America Merrill Lynch.

Wheeler, L. B. (1994). Changes in consensus earnings estimates and their impact on stock returns. In B. Bruce & C. B. Epstein (Eds.), *The handbook of corporate earnings analysis*. Chicago, IL: Probus.

Williams, J. B. (1938). *The theory of investment value*. Cambridge, MA: Harvard University Press.

Ziemba, W. T., & Schwartz, S. (1992). *Invest Japan*. Chicago, IL: Probus Publishing Co.

How to cite this article: Guerard J, Markowitz H. The existence and persistence of financial anomalies: What have you done for me lately? *Financial Planning Review*. 2018;1:e1022. https://doi.org/10.1002/cfp2.1022