CHAPTER 2

GLOBAL EARNINGS FORECASTING EFFICIENCY ☆

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ABSTRACT

Stock selection models often use momentum and analysts' expectation data. We find that earnings forecast revisions and direction of forecast revisions are more important than analysts' forecasts in identifying mispriced securities. Investing with expectations data and momentum variables is consistent with maximizing the geometric mean and Sharpe ratio over the long run. Additional evidence is revealed that supports the use of multifactor models for portfolio construction and risk control. The anomalies literature can be applied in real-world portfolio construction in the U.S., international, and global equity markets during the 1998–2009 time period. Support exists for the use of tracking error at risk estimation procedures.

While perfection cannot be achieved in portfolio creation and modeling, the estimated model returns pass the Markowitz and Xu data mining corrections test and are statistically different from an average financial model that could have been used to select stocks and form portfolios. We found additional evidence to support the use of Arbitrage Pricing Theory (APT) and statistically-based and fundamentally-based multifactor models for portfolio construction and risk control. Markets are neither efficient nor grossly inefficient; statistically significant excess returns can be earned.

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Stock selection models often use momentum and analysts' expectation data. We find that revisions and direction of forecast revisions are more important than analysts' forecasts in identifying mispriced securities. Our research and analysis revealed continued support for composite modeling using momentum and analysts' forecast variables using these sources of data for the U.S., international, and global equities during the 1998–2009 time period. We found additional evidence to support the use of Arbitrage Pricing Theory (APT) and statistically-based and fundamentally-based multifactor models (MFMs) for portfolio construction and risk control. Markets are neither efficient nor grossly inefficient. Statistically significant excess returns can be earned.

This study addresses several aspects of stock selection and portfolio construction. Momentum and analysts' forecasts are used to create mean–variance (MV) and equally actively weighted (EAW) portfolios for the U.S., international, and global stock markets over the 1998–2009 period. Knowledge of earnings forecasts, revisions, and breadth are important considerations to the stock selection and portfolio construction process. Momentum has long been associated with excess returns in stock selection models. Analysts' earnings per share (eps) forecasts, their revisions, and breadths are associated with excess returns. The relevance of analysts' forecasts and the implication for capital market efficiency has been surveyed in Brown (1993) and Ramnath, Rock, and Shane (2008). The original study of analysts' forecasts and revisions is Elton, Gruber, and Gültekin (1981). In this study, we briefly review traditional Markowitz portfolio selection, discuss the estimation and creation of expected returns, create efficient portfolios, and discuss the role of eps forecasts in portfolio selection.

Individual investors must be compensated for bearing risk. It is somewhat intuitive that the risk of a security should be directly linked to its rate of return. Investors want to secure the maximum return for a given level of risk, or the minimum risk for a given level of return. The concept of risk–return analysis is known as the efficient frontier, constructed by Markowitz (1952, 1959) and Bloch, Guerard, Markowitz, Todd, and Xu (1993). In this analysis, we created portfolios using a statistically based principal component analysis model, and attribute portfolio excess returns according to a fundamentally based multifactor risk model.

UNDERSTANDING RISK AND PORTFOLIO CONSTRUCTION

The Markowitz portfolio construction approach endeavors to identify the efficient frontier, the point at which returns are maximized for a given level of risk, or risk is minimized for a given level of return. The portfolio expected return, $E(R_p)$, 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:

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

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

The Markowitz framework defines risk as the portfolio standard deviation, its measure of dispersion (total risk). One seeks to minimize covariances in the Markowitz framework, holding constant expected returns. However, as the number of securities, N, increased, the number of covariances increased at a faster rate, with covariances being $N \times N-1$. Implicit in the development of the Capital Asset Pricing Model (CAPM) by Sharpe (1963, 1964), Lintner (1965), and Mossin (1966) is that investors are compensated for bearing market risk, or systematic risk, as measured by the stock beta. Systematic risk cannot be diversified away, whereas firm-specific risk, or unsystematic risk, can be diversified away. The beta is the slope of the market model in which the stock return is regressed as a function of the market return. An investor is not compensated for bearing risk that may be diversified away from the portfolio.

The CAPM holds that the return to a security is a function of the security's beta:

$$R_{jt} = R_F + \beta_j [E(R_{Mt}) - R_F] + e_j \tag{3}$$

where R_{jt} = expected security return at time t, $E(R_{Mt})$ = expected return on the market at time t, R_F = risk-free rate, β_j = security's beta, and e_j = randomly distributed error term.

The estimation of the CAPM beta, the measure of systematic risk, involves an ordinary least squares regression of the form:

$$\beta_j = \frac{\mathrm{Cov}(R_j, R_M)}{\mathrm{Var}(R_M)} \tag{4}$$

The security beta is the linear relationship between the security return and market return. The CAPM continues to be relevant in financial markets, as is reported. The difficulty of measuring beta and its corresponding SML gave rise to extramarket measures of risk found in the work of King (1966), Farrell (1974, 1997), Rosenberg (1974), Rosenberg and Marathe (1979), Stone (1974), Stone and Guerard (2010), Ross (1976), Ross and Roll (1980), Roll and Ross (1984), Chen, Ross, and Roll (1986), Blin, Bender, and Guerard (1997), Guerard, Gultekin, and Stone (1997), and Grinhold and Kahn (2000). In addition, Conner and Korajczyk (2010) provide an outstanding survey of the multifactor modeling and construction of portfolios.

King (1966) began much of the multifactor modeling work with his analysis of industries. Rosenberg (1974) made substantial progress in estimating the covariance matrix of security returns to address the sources of comovement in security returns. Rosenberg and Marathe (1979) published their seminal test of capital asset pricing in the first volume of this series. Rosenberg identified the covariance matrix in terms of common sources in security returns, the variances of security-specific returns, and estimates of the sensitivity of security returns to the common sources of variation in their returns, creating the Barra risk model which is now the industry standard for multifactor risk modeling. First, we will review the basic structure of the Barra risk model because the risk–return attrition analysis in this chapter is based on the Barra U.S. equity risk model.

Barra Model Mathematics

As an MFM, the Barra risk model builds on single-factor models by including and describing the interrelationships among factors.[1] The equation for single-factor models that describes the excess rate of return is written as:

$$\tilde{r}_j = \beta_j \tilde{f}_j + \tilde{u}_j \tag{5}$$

where $\tilde{r}_j$ = total excess return over the risk-free rate, β_j = sensitivity of security j to the factor, $\tilde{f}_j$ = rate of return on the factor, and $\tilde{u}_j$ = nonfactor (specific) return on security j.

This model can be expanded to include K factors. The total excess return equation for a multiple-factor model becomes:

$$\tilde{r}_j = \sum_{k=1}^{K} \beta_{jk} \tilde{f}_k + \tilde{u}_j \tag{6}$$

where β_{jk} = risk exposure of security j to factor k and $\tilde{f}_k$ = rate of return on factor k.

Note that when $K = 1$, the MFM equation reduces to the earlier single-factor version, the CAPM previously addressed.

The Rosenberg MFM framework was developed and estimated in Rosenberg's study with Marathe (Rosenberg & Marathe, 1979) and the Rosenberg extramarket component study (Rosenberg, 1974), in which security-specific risk could be modeled as a function of financial descriptors, or known financial characteristics of the firm. The following were the financial characteristics statistically associated with beta between 1954 and 1970:

- latest annual proportional change in eps;
- liquidity, as measured by the quick ratio;
- leverage, as measured by the senior debt-to-total assets ratio;
- growth measure of eps;
- book-to-price ratio;
- historic beta;
- logarithm of stock price;
- standard deviation of eps growth;
- gross plant per dollar of total assets;
- share turnover.

Rudd and Rosenberg (1979) and Menchero, Morozov, and Shepard (2010) expanded upon the initial Rosenberg MFM framework. The statistically significant determinants of the security systematic risk became the basis of the Barra E1 (USE1) Model risk indexes. The current (when this chapter was written) domestic MSCI Barra E3 (USE3) Model uses 13 sources of factor, or systematic, exposures: volatility, momentum, size, size nonlinearity, trading activity, growth, earnings yield, value, earnings variation, leverage, currency sensitivity, dividend yield, and nonestimation universe. In September 2011, MSCI released its Barra US Equity Model (USE4), developed and discussed in its empirical notes by Lin, Menchero, Orr, and Wang (2011). The USE4 Model is quite similar to the USE1 Model in that its style factors are beta, momentum, size, earnings yield, residual volatility, growth, book-to-price, leverage, liquidity, non-linear size, and non-linear beta. In January 2012, MSCI Barra released its Barra Global Equity Model (GEM3) with beta, momentum, size, earnings yield, residual volatility, growth, dividend yield, book-to-price, leverage, liquidity, and non-linear size. See Morozov, Wang, Borda, and Menchero (2012) for the empirical notes on the GEM3 Model. We discuss the Barra model because it is a widely used tool for assessing asset selection in portfolio construction, as we will do in section "Efficient Portfolio Construction." The reader is referred to Rudd and Clasing (1982) and Grinold and Kahn (1999) for complete discussions of the Barra System.

EXPECTED RETURNS MODELING AND STOCK SELECTION

Expected returns on assets are not completely explained solely by only using historical means (and standard deviations) in the United States and Japan. Practitioners on Wall Street traditionally have used reported financial data, momentum data, and earnings expectations data to estimate stock selection models and expected returns for individual securities. The earliest approaches to security analysis and stock selection involved the use of valuation techniques using reported earnings and other financial data. Graham and Dodd (1934) recommended that stocks be purchased on the basis of the price–earnings (P/E) ratio. The association of historical earnings and forecasted earnings in determining stock and portfolio returns continues to be relevant, as one finds when one examines the Barra earnings yield risk index in USE3.

Earnings forecasting enhances returns relative to using only reported financial data and valuation ratios. In 1975, a database of eps forecasts was created by Lynch, Jones, and Ryan, a New York brokerage firm, by collecting and publishing the consensus statistics of one-year-ahead and two-year-ahead eps forecasts (Brown, 2000). The database evolved to become known as the Institutional Brokerage Estimation Service (I/B/E/S) database. There is extensive literature regarding the effectiveness of analysts' earnings forecasts, earnings revisions, earnings forecast variability, and breadth of earnings forecast revisions, summarized in Bruce and Epstein (1994), Brown (1993, 2000, 2008), Ramnath et al. (2008), and Elton, Gruber, Brown, and Goetzman (2007). The vast majority of the earnings forecasting research in the Bruce and Brown references find that the use of earnings forecasts does not increase stockholder wealth, as specifically tested in Elton, Gruber, and Gültekin (1981) in their consensus forecasted growth variable, FGR. Reported earnings follow a random walk with drift process, and analysts are rarely more accurate than a no-change model in forecasting eps (Cragg & Malkiel, 1968). Analysts become more accurate as time passes during the year, and quarterly data are reported. Analyst revisions are statistically correlated with stockholder returns during the year (Arnott, 1985; Hawkins, Chamberlain, & Daniel, 1984). Wheeler (1994) developed and tested a 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. A composite earnings variable, E', is calculated using equally weighted revisions, EREV, forecasted earnings yields, FEP, and breadth, EB, of FY1 and FY2 forecasts, a variable put forth in Guerard (1997) and further tested in Guerard, Gültekin, and Stone (1997) and Guerard and Mark (2003).

Adding I/B/E/S variables to the eight value ratios in Guerard and Takano (1991) produced more than 2.5 percent of additional annualized return (Guerard et al., 1997). The finding of significant predictive performance value for I/B/E/S variables indicates that analyst forecast information has value beyond purely statistical extrapolation of past value and growth measures. Possible reasons for the additional performance benefit could be that analysts' forecasts and forecast revisions reflect information in other return-pertinent variables, discontinuities from past data, or serve as a quality screen on otherwise out-of-favor stocks. The quality screen idea confirms Graham and Dodd's argument that value ratios should be used in the context of the many qualitative and quantitative factors they argue are essential to informed investing. To test the risk-corrected performance value of the forecasts, Guerard et al. (1997) formed quarterly portfolios with risk being modeled via a four-factor APT-based model (created using five years of past monthly data). The portfolio quarterly returns averaged 6.18 percent before correcting for risks and transaction costs with excess returns of 3.6 percent after correcting for risk and 2.6 percent quarterly after subtracting 100 basis points to reflect an estimate of two-way transactions costs.[2]

Momentum investing was studied by academics at about the same time that earnings forecasting studies were being published. Arnott and Brush and Boles (1983) found statistically significant power in relative strength variables. The Brush and Boles analysis was particularly valuable because it found that the short-term (3-month) financial predictability of a naïve monthly price momentum model, taking the price at time $(t-1)$ divided by the price 12 months ago $(t-12)$, was as statistically significant in identifying underpriced securities as using the alpha of the market model adjusted for the security beta. Brush and Boles found that beta adjustments slightly enhanced the predictive power in the 6- to 12-month periods. Brush (2001) is an excellent 20-year summary of the price momentum literature. Fama and French (1992, 1995, 2008) used a price momentum variable using the price 2 months ago divided by the price 12 months ago, thus avoiding the well-known return or residual reversal effect. The academic momentum studies of Chan, Jegadeesh, and Lakonishok (1996, 1999) and Conrad and Kaul (1989, 1998) are very well known. Most momentum studies find significant stock price anomalies, even incorporating using transactions costs (Korajczyk & Sadka, 2004). The vast majority find that the use of 3-, 6-, and 12-month price momentum variables, often defined as intermediate term variables, is statistically significant and associated with excess returns and the most recent one-week or one-month returns create a residual return variable statistically negatively associated with stockholder returns. Brush (2001) reports that the quarterly information coefficient (IC) of the three-month price momentum variable exceeds its monthly IC, 0.073 versus 0.053. Guerard, Chettiappan, and Xu (2010) report a stock selection model, MQ, which combined momentum and CTEF, referred to as E' or CIBF in Guerard et al. (1997), in a composite model. One of the differences in this analysis and that of Guerard et al. (2010) is that the price momentum variable was separated into distinct price momentum and standard deviation variables which produce an enhanced (proprietary) MQ model, denoted MQ. The MQ variable is a proprietary model composed of a price momentum variable, PM, defined as the price one month ago divided by the price seven months ago, E', and the stock standard deviation.

We briefly surveyed the academic literature on anomalies and found substantial evidence that valuation, earnings expectations, and price momentum variables are significantly associated with security returns. Further evidence on the anomalies is found in Levy (1999).[3]

EFFICIENT PORTFOLIO CONSTRUCTION

Efficient portfolio construction is concerned with creating portfolios offering the greatest return for a given level of risk. The MQ model can be input into the APT system to create optimized portfolios. By varying the tolerance or risk-aversion, or lambda, the efficient frontier is created. The MQ model is our approximation of the expected return, or the forecast active return, α, of the portfolio. Industry researchers typically apply the Markowitz mean/variance framework to active management, as described in Grinold and Kahn (1999):

$$U = \alpha \cdot h - \lambda \cdot \omega^2 \cdot h^2 \tag{7}$$

Here α is the forecast active return (relative to a benchmark which can be cash), ω is the active risk, and h is the active holding (the holding relative to the benchmark holding). By varying the tolerance or risk-version, one can create the efficient frontier in the APT model, as was done in Bloch et al. (1993), by varying the variable m. The risk-aversion parameter, λ, captures individual investor preference. There are several criteria to be used in portfolio construction. First, the geometric mean (GM) of the portfolio is maximized over time (Latane, 1959; Markowitz, 1959, 1976, 2002). The Sharpe ratio (ShR; Sharpe, 1966, 1970, 1994) should be maximized. Grinold and Kahn (1999) use the information ratio (IR) as a portfolio construction objective to be maximized, which measures the ratio of residual return to residual risk:

$$\mathrm{IR} \equiv \frac{\alpha}{\omega} \tag{8}$$

In this analysis, we created portfolios that maximize the GM, ShR, and IR.

We constructed an equal active weighting (EAW) efficient frontier varying the risk-aversion levels. The EAW process allows security weights in the portfolio to deviate no more than 2 percent from the benchmark weights, a process based on Markowitz's enhanced index tracking (EIT) procedure. Guerard, Takano, and Yamane (1993) created portfolios using MV and EIT portfolio construction procedures. The portfolio construction process uses 8 percent monthly turnover, after the initial portfolio is created, and 150 basis points of transactions costs each way, globally, 125 basis points, domestically. The MQ optimized portfolios outperform the U.S. market. Guerard et al. (1993) tested a variation of the Markowitz (1987) optimization within security weight bounds is enhanced (defined here as the Russell 3000 Growth (R3G) Index), and the global market benchmarks (defined here as the Morgan Stanley Capital International (MSCI) All Country World Growth (ACWG) Index). The index returns are often referred to as the benchmark, denoted B (see Chart 1).

The inefficiencies of the international and global markets, relative to the U.S. market, are illustrated in Chart 1 in the increased returns relative to the risk of investing in other markets.

The analyst-covered stocks in the United States are ranked on monthly MQ-based criteria from January 1998 to December 2009. The sources of the MQ enhanced excess returns are exposures to size (buying smaller capitalized securities), earnings yield, financial leverage, value, momentum risk indexes, and asset selection (see Tables 1 and 2). Asset selection is statistically significant at the 10 percent level in the R3G universe for the 1998–2009 time period for a lambda of 500 estimation.

The analyst-covered stocks in the Global market are ranked on monthly MQ-based criteria from January 1998 to December 2009. The sources of the MQ enhanced excess returns are exposure to size (buying smaller capitalized securities), success and value risk indexes, and asset selection (see Tables 3 and 4 for a lambda = 500 estimation).[4]

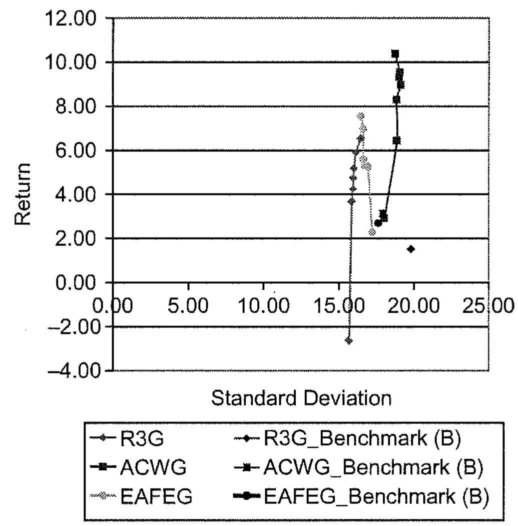

Chart 1. EAW MCM Efficient Frontier, January 1998 to December 2009. *Source*: Zephyr Style Advisor, May 13, 2010.

Table 1. MQ Analysis in Russell 3000 Growth Universe, Attribution Report, February 1998 to December 2009 (Annualized Contributions to Total Return).

Source of Return	Contribution (Percent Return)	Risk (Percent Standard Deviation)	Information Ratio	*t*-Statistics
1. Risk free	3.09			
2. Total benchmark	1.31	19.74		
3. Expected active	−1.38			
4. Market timing	3.77	8.26	0.35	1.22
5. Risk indices	4.17	7.22	0.54	1.87
6. Industries	−1.37	7.56	−0.16	−0.57
7. Asset selection	2.69	5.52	0.49	1.71
8. Trading				
9. Transaction cost	−3.29			
10. Total exceptional active (4 + · · · + 9)	5.97	13.62	0.38	1.32
11. Total active (3 + 10)	4.59	13.62	0.28	0.98
12. Total managed (2 + 11)	5.90	16.59		

Source: MSCI Barra Attribution Report, May 13, 2010.

Table 2. MQ Analysis and Russell 3000 Growth, Attribution Report (Annualized Contributions to Risk Index Return).

Source of Return	Average Active Exposure	Contribution (Percent Return)			Total		
		Average (1)	Variation (2)	Total (1 + 2)	Risk (Percent Standard Deviation)	Information Ratio	*t*-Statistics
Volatility	−0.22	−0.49	−0.39	−0.89	2.09	−0.41	−1.44
Momentum	0.37	−0.78	−0.27	−1.05	4.12	−0.27	−0.92
Size	−1.31	3.50	0.89	4.39	6.21	0.69	2.40
Size nonlinearity	−0.41	−0.26	−0.18	−0.44	2.37	−0.22	−0.76
Trading activity	−0.16	0.04	−0.20	−0.17	1.09	−0.17	−0.59
Growth	−0.30	0.20	0.00	0.20	0.78	0.22	0.77
Earnings yield	0.78	2.34	−0.03	2.32	3.03	0.75	2.60
Value	0.57	−0.18	0.11	−0.07	1.22	−0.04	−0.12
Earnings variation	0.18	−0.16	0.11	−0.05	0.50	−0.08	−0.29
Leverage	0.59	−0.86	0.52	−0.34	1.39	−0.22	−0.78
Currency sensitivity	−0.12	−0.02	0.04	0.02	0.65	0.05	0.17
Yield	0.40	−0.17	0.28	0.11	0.99	0.07	0.25
Nonestimation universe	0.09	0.07	0.07	0.14	1.02	0.10	0.36
Total				4.17	7.22	0.54	1.87

Source: MSCI Barra Attribution Report, May 13, 2010.

Table 3. MQ Analysis in the Global Growth Universe, Attribution Report, February 1998 to December 2009 (Annualized Contributions to Total Return).

Source of Return	Contribution (Percent Return)	Risk (Percent Standard Deviation)	Information Ratio	*t*-Statistics
1. Risk free	2.47			
2. Total benchmark	4.46	18.54		
3. Country selection	3.65	5.17	0.64	1.93
4. Currency selection	1.39	2.09	0.63	1.93
5. Cash–equity policy	0.01	0.01	0.37	1.11
6. Asset allocation (3 + 4 + 5)	5.04	5.53	0.83	2.54
7. Local market timing	−1.21	3.04	−0.48	−1.45
8. Risk indices	2.04	3.55	0.55	1.68
9. Industries	1.75	2.32	0.69	2.11
10. Asset selection	5.90	3.27	1.66	5.06
11. Within market (7 + 8 + 9 + 10)	8.48	6.40	1.18	3.59
12. Trading				
13. Transaction cost	−2.97			
14. Total active (6 + 11 + 12 + 13)	10.58	7.94	1.22	3.71
15. Total managed (2 + 14)	15.04	18.26		

Source: MSCI Barra Attribution Report, June 13, 2010.

Table 4. MQ Analysis in the Global Growth Universe, Attribution Report, February 1998 to December 2009 (Annualized Contributions to Risk Index Return).

Source of Return	Average Active Exposure	Contribution (Percent Return)			Total		
		Average (1)	Variation (2)	Total (1 + 2)	Risk (Percent Standard Deviation)	Information Ratio	*t*-Statistics
Size	−0.59	1.43	0.31	1.74	1.69	0.98	2.97
Success	0.72	−1.98	0.45	−1.52	3.40	−0.39	−1.18
Value	0.43	1.46	0.54	2.01	1.11	1.62	4.94
Variability in markets	0.09	−0.18	−0.01	−0.19	0.48	−0.37	−1.11
Total				2.04	3.55	0.55	1.68

Source: MSCI Barra Attribution Report, June 13, 2010.

One estimates the Markowitz efficient frontier by varying the lambda, the measure of risk-aversion. As lambda increases, so does the riskiness of the portfolio. In the case of the MQ variable, one buys smaller capitalized (sized) stocks which tend to produce potentially higher asset selection and total returns. The smaller stocks have more exposures to momentum (success in the Barra GEM model). The lambda = 500 portfolios maximize the GM, asset selection, and Total Active Return (TAR), in the MQ variable in domestic and global universes (Table 5).

Asset selection of the MQ model is statistically significant at the 5 percent level in the ACWG universe in the 1998–2009 time period and exceeds the asset selection of the MQ model in the R3G universe. Global markets have historically been more inefficient than the U.S. markets (Bloch et al., 1993). In summary, the MQ selection model produces asset selection of 269 basis points (statistically significantly at the 10 percent level) in the United States and 590 basis points in the Global market (statistically significantly at the 5 percent level) during the November 2000 to December 2009 time period; emerging markets (EM) became an investable universe for many investors and EM expanded the risk–return trade-off of MCM investors (Chart 2). Documentation for the McKinley Capital Mangement, LLC, can be found in its white papers of June and August 2006.

ADDITIONAL EVIDENCE ON TRACKING ERROR AT RISK AND EFFICIENT PORTFOLIO CONSTRUCTION

We can decompose the MQ variable into (1) price momentum, (2) the consensus analysts' forecasts efficiency variable, CIBF, identified in Guerard et al. (1997), which itself is composed of forecasted earnings yield, EP, revisions, EREV, and direction of revisions, EB, identified as breadth, and (3) the stock standard deviation, identified in Malkiel (1963) as a variable with predictive power regarding the stock P/E multiple. Guerard et al. (1997) and Guerard and Mark (2003) found that the consensus analysts' forecast variable dominated analysts' forecasted earnings yield, as measured by I/B/E/S one-year-ahead forecasted earnings yield, FEP, revisions, and breadth. We find evidence to support Guerard et al. and Guerard and Mark domestically that the predicted earnings yield is incorporated into the stock price through the earnings yield risk index. Moreover, CIBF dominates the historic low price-to-earnings effect, or high earnings-to-price, PE.

Table 5. MQ, Equal Active Weighting (EAW) Portfolio Construction, and the Estimated ACWG and R3G Efficient Frontiers, January 1998 to December 2009.

Lambda	Risk Indices	*t*-Statistics	ACWG Asset Selection	*t*-Statistics	Total Active Return	*t*-Statistics	Success	Barra Risk Exposures Size
500	2.04	1.68	5.90	5.06	10.58	3.71	0.72	−0.59
200	2.32	1.93	5.26	4.75	9.47	3.58	0.71	−0.60
100	2.50	2.13	4.46	4.29	7.69	3.20	0.70	−0.59
75	2.32	1.98	3.99	3.92	6.69	2.85	0.69	−0.56
50	2.12	1.96	3.89	3.90	5.94	2.64	0.68	−0.55
10	0.51	0.45	5.27	6.77	7.39	3.32	0.68	−0.52
1	−1.74	−2.42	1.41	2.25	−3.76	−2.65	0.32	0.04
Lambda	**Risk Indices**	***t*-Statistics**	**R3G Asset Selection**	***t*-Statistics**	**Total Active Return**	***t*-Statistics**	**Momentum**	**Barra Risk Exposures Size**
500	4.17	1.87	2.69	1.71	4.59	0.98	0.37	−1.31
200	3.78	1.88	2.59	1.75	3.95	0.91	0.37	−1.29
100	3.31	1.78	1.98	1.40	3.19	0.74	0.36	−1.13
75	3.15	1.75	1.79	1.30	3.88	0.98	0.36	−1.09
50	2.98	1.75	1.42	1.09	2.30	0.52	0.36	−1.02
10	2.25	1.63	1.59	1.44	2.77	0.79	0.30	−0.80
1	1.20	1.26	0.83	1.15	−1.92	−1.24	0.12	−0.41

Source: MSCI Barra Attribution Analysis, August 10, 2010.

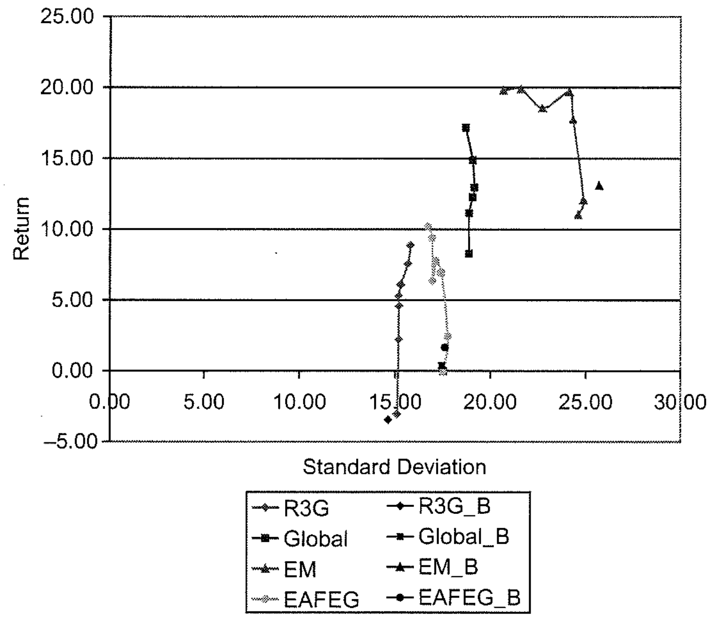

Chart 2. EAW Trade-Off Analysis, November 2000 to December 2009. *Source*: Zephyr Style Advisor, May 13, 2010.

The reader is referred to Chart 3, for the R3G analysis. Again, 125 basis points of transactions costs, each way, are charged and the portfolios are constructed with 8 percent monthly turnover and 4 percent maximum security weights. A position threshold (a minimum buy-in position) of 35 basis points is used.

The estimation of security weights, x, 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. As previously discussed, the security weight is the proportion of the portfolio's market value invested in the individual security:

$$x_s = \frac{\mathrm{MV}_s}{\mathrm{MV}_\mathrm{p}} \tag{9}$$

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

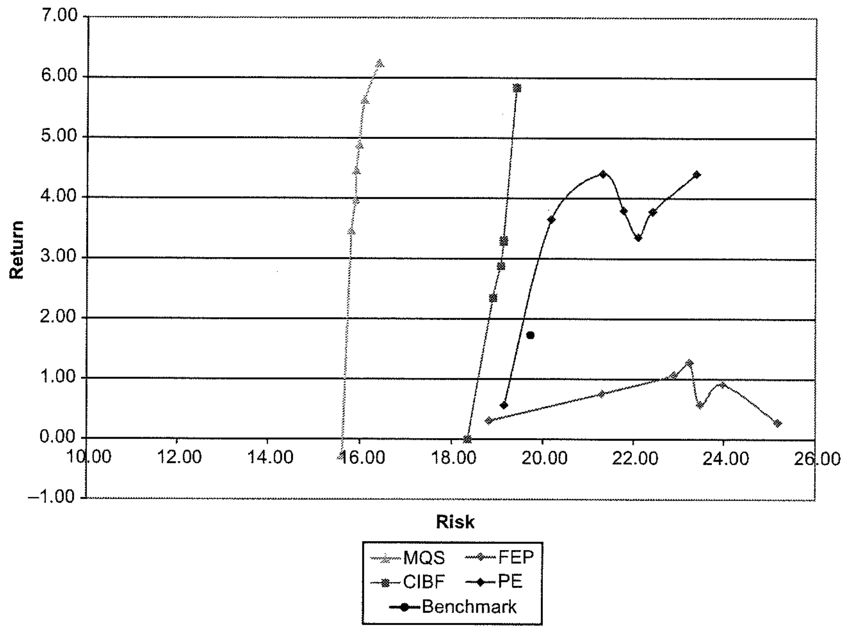

Chart 3. MCM USE3 Earnings Forecasting Analysis, January 1998 to December 2009. *Source*: Zephyr Style Advisor, August 25, 2010.

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:

$$x_{s,\mathrm{p}} - x_{s,\mathrm{b}} \tag{10}$$

Accordingly, if IBM has a 3 percent weight in the portfolio while its weight in the benchmark index is 2.5 percent, then IBM has a positive, 50 basis points active weight in the portfolio. The portfolio manager has an active, positive opinion of securities on which he or she has a positive active weight and a negative opinion of those securities with negative active weights.

Markowitz analysis (1952, 1959) and its efficient frontier minimized risk for a given level of return. Risk can be measured by a stock's volatility, or the standard deviation in the portfolio return over a forecast horizon, normally one year:

$$\sigma_{\mathrm{p}} = \sqrt{E(r_{\mathrm{p}} - E(r_{\mathrm{p}}))^2} \tag{11}$$

Blin and Bender created Advanced Portfolio Technologies (APT), a firm dedicated to applying the Arbitrage Pricing Theory (APT) Model techniques in 1985, and Published its *Analytics Guide* (2005). The mathematical foundations of their APT system, was published in Blin et al. (1997). The following analysis draws upon the APT analytics. Volatility can be broken down into systematic and specific risk:

$$\sigma_{\mathrm{p}}^2 = \sigma_{\beta \mathrm{p}}^2 + \sigma_{\varepsilon \mathrm{p}}^2 \tag{12}$$

where σ_{p} = total portfolio volatility, $\sigma_{\beta\mathrm{p}}$ = systematic portfolio volatility, and $\sigma_{\varepsilon\mathrm{p}}$ = specific portfolio volatility.

Blin and Bender created a multifactor risk model within their APT risk model based on forecast volatility:

$$\sigma_{\mathrm{p}} = \sqrt{52\left(\sum_{c=1}^{C}\left(\sum_{i=1}^{S} x_i \beta_{i,c}\right)^2 + \sum_{i=1}^{s} x_i^2 \varepsilon_{i,w}^2\right)} \tag{13}$$

where σ_{p} = forecast volatility of annual portfolio return, C = number of statistical components in the risk model, x_i = portfolio weight in security i, $\beta_{i,c}$ = the loading (beta) of security i on risk component c, and $\varepsilon_{i,\mathrm{w}}$ = weekly specific volatility of security i. The APT test statistics were reported in Blin, Bender, and Guerard (1997).

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

$$\sigma_{\mathrm{te}} = \sqrt{52\left(\sum_{c=1}^{C}\left(\sum_{i=1}^{S} x_{i,\mathrm{p}} - x_{i,\mathrm{b}}\right)\beta_{i,c}\right)^2 + \sum_{i=1}^{s}(x_{i,\mathrm{p}} - x_{i,\mathrm{b}})^2 \varepsilon_{i,w}^2} \tag{14}$$

where $x_{i,\mathrm{p}} - x_{i,\mathrm{b}}$ = portfolio active weight.

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

$$\sigma_{\beta\text{te}} = \sqrt{52 \sum_{c=1}^{C} \left(\sum_{i=1}^{S} (x_{i,\text{p}} - x_{i,\text{b}}) \beta_{i,c}^{2} \right)} \tag{15}$$

The portfolio Value-at-Risk (VaR) is the expected maximum loss that a portfolio could produce over one year:

$$\text{VaR} = \upsilon_{\text{p}} = \tilde{V}_{\text{T}}, \quad \text{given prob } (V_{\text{T}} < \tilde{V}_{\text{T}}) = c \tag{16}$$

where V_{T} = actual potential portfolio value in one year, $\tilde{V}_{\text{T}}$ = potential portfolio value in one year, and c = desired confidence level for VaR (i.e., 95 percent).

If a portfolio return is assumed to be generated from a normal distribution, then

$$\upsilon_{\text{p}} = \sqrt{2}\,\text{erf}^{-1}(2_x - 1)\sigma_{\text{p}} V_0 \tag{17}$$

where $\text{erf}^{-1}(x)$ = inverse error function and V_0 = current portfolio value.

The APT-calculated VaR is written as follows:

$$\upsilon_{\text{p}} = \sqrt{2}\,\text{erf}^{-1}(2_x - 1)\left(\sqrt{52\left(\sum \left(\sum x_i \beta_{i,c} \right)^2 + \sum x_i^2 \varepsilon_{i,w}^2 \right)} \right) V_0 \tag{18}$$

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 Tracking-at-Risk™ (TaR):

$$T_{\text{p}}^{V} = \sqrt{\left(\frac{1}{\sqrt{1-x}} \sigma_s \right)^2 + (\sqrt{2}\,\text{erf}^{-1}(x)\sigma_\varepsilon)^2} \tag{19}$$

where T_{p}^{V} = TaR™, x = desired confidence level of TaR™, σ_s = portfolio systematic tracking error, $\text{erf}^{-1}(x)$ = inverse error function, and σ_ε = portfolio-specific tracking error.

Blin et al. (1997), estimated a 20-factor beta model of covariances based on 2.5 years of weekly stock returns data. The Blin and Bender APT model followed the Ross factor modeling theory, but Blin and Bender estimated betas from at least 20 orthogonal factors. Blin and Bender never sought to identify their factors with economic variables.

Guerard et al. (2010) found that the APT–Tracking Error at Risk (TaR) estimation procedure helped in creating 130/30 portfolios relative to traditional Markowitz MV and EAW portfolios. Are alternative portfolio techniques appropriate in the U.S. and global universes during the 1997–2009 time period? We construct EAW with 2 percent deviations (EAW2), MV (with a 4 percent maximum weight), and Mean–Variance Tracking Error at Risk (MV TaR) portfolios for January 1997 to December 2009 using 8 percent monthly turnover, after the initial portfolio is created, and 150 basis points of transactions costs each way. Comparing EAW, MV, and MV TaR provides support for the MV TaR procedure in the United States, as MV TaR maximizes the GM, ShR, and IR relative to EAW and MV. In the global universe, MV TaR maximizes the GM and ShR. EAW maximizes the IR in Global markets over this time period (Table 6).

The MV TaR portfolio construction methodology consistently outperforms traditional MV and EAW portfolio construction methodologies at all lambda values in asset selection and TARs, by producing larger exposure to momentum (Table 7).

One may ask why combine momentum, PM, and analysts' expectations of earnings, *E′*? Is momentum a sufficient strategy for asset selection in the United States? What do earnings forecasts and revisions of earnings acceleration have to do with effective portfolio construction, particularly if analysts' forecasts are not better than a random walk with drift model? Our research provides the following response. Let us examine the U.S.-listed securities from January 1998 to December 2009, using an 8 percent monthly turnover constraint and subtracting 125 basis points (each way), annually. Price momentum produces positive asset selection, as reported in Table 8,

Table 6. APT-Created Lambda = 500 Portfolios, January 1997 to December 2009.

Universe	Portfolio Estimation	Geometric Mean (GM)	Sharpe Ratio (ShR)	Information Ratio (IR)
R3G	EAW	6.54	0.17	0.33
	MV	7.02	0.23	0.35
	MV TaR	7.57	0.26	0.40
ACWG	EAW	12.53	0.41	0.70
	MV	12.26	0.48	0.66
	MV TaR	12.58	0.48	0.61

Source: Zephyr Style Advisor, June 14, 2010.

Table 7. MQ, R3G Alternative Portfolio Construction Methodologies, January 1998 to December 2009.

Lambda	Risk Indices	*t*-Statistics	Asset Selection	*t*-Statistics	Total Active Return	*t*-Statistics	Momentum	Barra Risk Exposures Size	Growth
EAW									
500	4.17	1.87	2.69	1.71	4.59	0.98	0.37	−1.31	−0.30
200	3.78	1.88	2.59	1.75	3.95	0.91	0.37	−1.29	−0.30
100	3.31	1.78	1.98	1.40	3.19	0.74	0.36	−1.13	−0.28
75	3.15	1.75	1.79	1.30	3.88	0.98	0.36	−1.09	−0.27
50	2.98	1.75	1.42	1.09	2.30	0.52	0.36	−1.02	−0.27
10	2.25	1.63	1.59	1.44	2.77	0.79	0.30	−0.80	−0.25
1	1.20	1.26	0.83	1.15	−1.92	−1.24	0.12	−0.41	−0.26
MV									
500	4.23	1.83	2.96	1.58	5.02	1.05	0.40	−1.36	−0.31
200	3.89	1.81	2.67	1.52	4.54	0.99	0.40	−1.26	−0.30
100	3.46	1.81	2.15	1.35	3.62	0.84	0.39	−1.15	−0.29
75	3.31	1.78	2.12	1.37	3.37	0.79	0.39	−1.12	−0.28
50	3.12	1.79	1.70	1.20	2.59	0.60	0.38	−1.07	−0.28
10	2.25	1.62	1.73	1.56	1.96	0.48	0.31	−0.81	−0.24
1	1.02	1.08	1.09	1.48	0.29	−0.12	0.10	−0.39	−0.25
MV TaR									
500	4.22	1.88	3.73	1.89	5.64	1.24	0.43	−1.37	−0.28
200	3.76	1.83	3.20	1.69	4.67	1.07	0.44	−1.23	−0.27
100	3.36	1.77	2.71	1.56	3.71	0.90	0.43	−1.16	−0.26
75	3.25	1.77	2.64	1.58	3.36	0.83	0.43	−1.14	−0.25
50	3.08	1.76	2.18	1.38	3.88	1.03	0.43	−1.09	−0.25
10	2.78	1.90	1.77	1.38	2.56	0.71	0.37	−0.91	−0.22
1	1.46	1.42	1.29	1.54	0.95	0.11	0.07	−0.44	−0.24

Source: MSCI Barra Attribution Analysis, August 10, 2010.

Table 8. MQ, R3G Price Momentum, Earnings Forecasts, and MQ Strategies, January 1998 to December 2009.

Lambda	Risk Indices	*t*-Statistics	EAW Asset Selection	*t*-Statistics	Total Active Return	*t*-Statistics	Momentum	Barra Risk Exposures Size	Growth
PM									
500	1.35	0.66	1.14	1.18	0.18	0.40	0.70	−1.55	0.45
200	1.20	0.63	1.46	1.45	0.37	0.45	0.68	−1.48	0.44
100	1.04	0.61	1.47	1.51	0.31	0.42	0.67	−1.43	0.44
75	1.18	0.71	1.74	1.74	0.64	0.54	0.65	−1.40	0.41
50	0.80	0.54	2.41	2.40	0.82	0.59	0.63	−1.34	0.40
E'									
500	4.41	2.39	3.71	3.06	4.11	1.78	0.27	−1.58	0.04
200	3.83	2.31	2.14	1.98	2.16	0.99	0.25	−1.44	0.04
100	3.35	2.30	1.89	1.95	1.60	0.81	0.25	−1.33	0.04
75	3.21	2.26	2.09	2.15	1.59	0.81	0.24	−1.27	0.03
50	2.98	2.25	1.72	1.88	1.17	0.60	0.23	−1.16	0.03
MQ									
500	4.17	1.87	2.69	1.71	4.59	0.98	0.37	−1.31	−0.30
200	3.78	1.88	2.59	1.75	3.95	0.91	0.37	−1.29	−0.30
100	3.31	1.78	1.98	1.40	3.19	0.74	0.36	−1.13	−0.28
75	3.15	1.75	1.79	1.30	3.88	0.98	0.36	−1.09	−0.27
50	2.98	1.75	1.42	1.09	2.30	0.52	0.36	−1.02	−0.27

Source: MSCI Barra Attribution Analysis, August 10, 2010.

with high positive Barra momentum and growth exposures, as expected. The momentum variable does not produce statistically significant asset selection at higher lambda values. The forecasted earnings acceleration variable, E', produces statistically significant risk index exposure returns (to smaller stocks and momentum) and asset selection. E' is not hampered by ineffective industry exposures, as is the PM process, that is, the risk indices of the E' variable are statistically significant, as is the asset selection. The E' variable is the US source of MQ asset selection. As the lambda rises, so does asset selection and its statistical significance. MQ produces statistically significant risk index returns (as did PM) and higher asset selection and total active returns than its primary components, PM and E'. Earnings acceleration complements price momentum.

CONCLUSIONS

Stock selection models often use momentum and analysts' expectation data. We find that revisions and direction of forecast revisions are more important than analysts' forecasts in identifying mispriced securities. Investing with expectations data and momentum variables is consistent with maximizing the GM and ShR over the long run. Additional evidence is revealed that supports the use of MFMs for portfolio construction and risk control. The anomalies literature can be applied in real-world portfolio construction in the U.S., international, and global equity markets during the 1998–2009 time period. Support exists for the use of tracking error at risk estimation procedures. While perfection cannot be achieved in portfolio creation and modeling, the MQ and MQ processes pass the Markowitz and Xu data mining corrections test. We found additional evidence to support the use of APT MFMs for portfolio construction and risk control. Markets are neither efficient nor grossly inefficient. Statistically significant excess returns can be earned.

NOTES

1. See the Barra (USE3) U.S. Equity, Version 3, *Risk Model Handbook*. See also Rosenberg and Marathe (1979), and Grinhold and Kahn (2000).
2. Guerard (2006) reported the growing importance of earnings forecasts, revisions, and breadth in Japan and the United States, particularly with respect to smaller capitalized securities.

3. R.A. Haugen and Baker (1996, 2010) extended their 1996 study in a recent volume to honor Harry Markowitz. Haugen and Baker estimate their model using weighted least squares. In a given month they estimated the payoffs to a variety of firm and stock characteristics using a weighted least squares multiple regression in each month in the period 1963–2007. In the manner of Fama and MacBeth (1973), they then compute the average values for the monthly regression coefficients (payoffs) across the entire period. Dividing the mean payoffs by their standard errors, we obtain *t*-statistics.

The values for the most significant factors are computed as follows:

- Residual return is last month's residual stock return unexplained by the market.
- Cash flow-to-price is the12-month trailing cash flow-per-share divided by the current price.
- Earnings-to-price is the 12-month trailing eps divided by the current price.
- Return on assets is the12-month trailing total income divided by the most recently reported total assets.
- Residual risk is the trailing variance of residual stock return unexplained by market return.
- Twelve-month return is the total return for the stock over the trailing 12 months.
- Return on equity is the 12-month trailing eps divided by the most recently reported book equity.
- Volatility is the 24-month trailing volatility of total stock return.
- Book-to-price is the most recently reported book value of equity divided by the current market price.
- Profit margin is the 12-month trailing earnings before interest divided by 12-month trailing sales.
- Three-month return is the total return for the stock over the trailing three months.
- Sales-to-price is 12-month trailing sales-per-share divided by the market price.

Last month's residual return and the return over the preceding three months have negative predictive power relative to next month's total return. This may be induced by the fact that the market tends to overreact to most information. The four measures of cheapness, cash-to-price, earnings-to-price, book-to-price, and sales-to-price, all have significant positive payoffs. R.A. Haugen and Baker (2010) find statistically significant results for the four fundamental factors as did the previous studies we reviewed. Haugen and Baker present optimization analysis to support their stock selection modeling, and portfolio trading is controlled through a penalty function. When available, the optimizations are based on the largest 1,000 stocks in the database. Estimates of portfolio volatility are based on the full covariance matrix of returns to the 1,000 stocks in the previous 24 months. Trading costs were not reflected in the Haugen and Baker optimization analysis; however, the Haugen and Baker portfolios outperformed the benchmark by almost 5 percent with average annual turnover of 80 percent during the 1965–2007 period. Haugen and Baker noted that the *t*-scores are large as compared to those obtained by Fama and MacBeth even though the length of the time periods covered by the studies is comparable. The R.A. Haugen and Baker (2010) analysis and results are consistent with the Bloch et al. (1993) model.

4. The author is aware of the Menchero et al. (2010) GEM2 Model introduced in 2009 to create global portfolios and access global performance. The attribution model used in Tables 3 and 4 was the MSCI Barra Global Equity Model, GEM model, because the GEM model existed at the time the McKinley Capital Management, LLC (MCM) global portfolio management and research was conducted.

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