Skewness and the Dialectic of Risk Premium

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Abstract. The following work is devoted to an account of time-series asset pricing. The author considers the origins of this line of empirical finance and proffers a Fama & French style study on returns in Switzerland, the United Kingdom and the United States over the last decade. The canonical three-factor model is conditioned on the book-to-market ratio to better explore the relationship to risk of the latter. Skewness is looked at as a potential proxy for the book-to-market ratio. The Harvey & Siddique conditional skewness factor is also considered in a context of market segmentation[1].

JEL Classification Codes: G15, G14, G11, G12
Key Words: Asset Pricing Models, Equity Markets, International Risk Factors, Market Efficiency, Anomaly, Arbitrage

Contents

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Modern Financial Theory has espoused the virtues of mean-variance optimization and the concomitant efficient market portfolio for nearly half a century. Returns were to be proportionate to a measure of the asset's contribution to the market's riskiness termed Beta. All other risk was irrelevant due the possibility of diversification. Manifestly non-market factors were to be viewed as components of the market itself. An onslaught of empirical refutation ensued. It was shown that non-systematic factors that were specific to the company and thus "diversifiable" played a greater role in explaining cross-sectional equity returns than the excess market.

Further questions arose regarding the testability of the model: what constituted proper Beta measurement and the selection of the market proxy? Attention was also focused on anomalies, the persistence of which would imply that either markets were inefficient or that asset pricing models were deficient. The burgeoning industry of non-market correlated assets was perhaps the nail in the coffin of the one-factor classical Capital Asset Pricing Model. In the subsequent phase of financial theoretical development, assets are more likely to be priced on a Security Market Hyperplane, the axes of which often best proxied by business cycle, distress likelihood related, and firm-specific factors.

The author's intention is not to kick a dead horse, but rather to see if it is still alive with the intent of bringing together pertinent strains of theory into a coherent overview which might shed light on avenues for future research. Further, the specific contribution of this document is the application of econometric techniques that allow for efficient coefficient estimation in the presence of regressions with correlated error terms and non-correlated exogenous factors to the trio of countries, the United States, the United Kingdom and Switzerland. The work thereby serves as a rebutal to previous pan-European analyses, specifically to that of Heston et al. (1997) and extends the empirical approach of Lewellen & Shanken (2000). The issue of skewness in general is addressed.

The document is structured as follows: Section 1-4 recapitulate the fundamentals of modern financial theory; Section 5 looks at the pertinent canonical empirical work; Section 7 contains the author's model fittings and results with Section 8 culminating the work.

1. Theoretical Foundations

Any enumeration of the significant developments in asset pricing models would not be complete without a perfunctory mention of the Arrow (1953) and Debreu's (1960) contingent claim pricing model and Farkas' Lemma (1902) of the non-simultaneity of arbitrage and pricing. Nevertheless, for the sake of brevity and consistency, this document will focus on the empirically tractable models which have characterized modern financial thought.

1.1. The Capital Asset Pricing Model. In 1952, Markowitz published "Portfolio Selection", his seminal work on portfolio creation based upon the principal of diversification in a mean-variance world. His approach was both quantitative and normative in nature. Inspired by Markowitz's "Efficient Frontier"[2] and Tobin's "Separation The-

[2] The Efficient Frontier refers to all portfolios which are optimized in terms of mean and variance.

orem"[3], Sharpe was able to assign to this mean-variance efficient portfolio a single risk factor through the intermediary of the following relationship:

$$\sigma(\widetilde{R}_p) = \sum_{i=1}^{N} x_{ip} \left[\frac{\sum_{j=1}^{N} x_{jp}\sigma_{ij}}{\sigma(\widetilde{R}_p)} \right] = \sum_{i=1}^{N} x_{ip} \frac{cov(\widetilde{R}_i, \widetilde{R}_p)}{\sigma(\widetilde{R}_p)} \tag{1}$$

where $\sigma(\widetilde{R}_p)$ refers to the standard deviation of a portfolio return of N securities of which i and j have portfolio proportions x_{ip} and x_{jp} with covariance σ_{ij}. Thus, the marginal contribution of security i to portfolio variance is its weighted covariance with the weighted portlolio components divided by the portfolio risk. Sharpe makes several assumptions to bring his Capital Asset Pricing Model (CAPM) to fruition, one of which is that every asset is held in positive quantities by the market portfolio, whence $p = m$, $\sigma(\widetilde{R}_p) = \sigma(\widetilde{R}_m)$ implies $\sum_{i=1}^{N} x_{im} = 1$. Knowing $\beta_{im} = \frac{cov(\widetilde{R}_i, \widetilde{R}_m)}{var(\widetilde{R}_m)}$ and $\beta_{mm} = 1$,we obtain $\sigma(\widetilde{R}_p) = \sigma(\widetilde{R}_p)\beta_{mm}$.

Consistent with this line of reasoning the investor is not to be remunerated for holding general risk–high standard deviation–rather the risk had to come from one source–the market portfolio–and the asset would earn a premium proportionate to its risk contribution to this market aggregate relative to the latter's riskiness. This relative risk measure was to be known as Beta, β_{im}. The more the asset risk covaried with that of the market, the greater a premium one would receive to compensate for the risk of a market downturn. Intuitively, holding assets that perform badly in already bleak states of nature warrants a risk premium. This linear premium is expressed as

$$\mathbf{E}(\widetilde{R}_i) - \mathbf{E}(\widetilde{R}_f) = \beta_{im}\{\mathbf{E}(\widetilde{R}_m) - \mathbf{E}(\widetilde{R}_f)\}^4 \tag{2}$$

The CAPM has the same set of assumptions that underpin the Tobin (1958) and Markowitz (1959) two-parameter normative portfolio model whereby investors have a one-period horizon and make decisions based on portfolio expected returns and standard deviations during that period[18]. Regarding preferences, modern portfolio theory posits investor non-satiability, risk-averse, and with time separable preferences. Preference hypotheses become redundant in the presence of the class of eliptical distributions for one-period percentage returns[5]. One assumes perfect capital markets[6] where investors are price takers and there is no arbitrage.

In addition to these prerequisite assumptions, the CAPM adds several others for the purpose of examining collective equilibrium market behavior: uniform horizons, uniform risk-free rate, uniform information access with no costs, and homogenous expectations regarding returns and the market covariance matrix. The final touch of a constant opportunity set makes the model complete.

[3] Here we refer to Tobin's theory that the decision to invest in a given proportion of stocks constituing the market portfolio is not influenced by risk preferences, because one can use leverage to increase or decrease effective risk exposure.

[4] More general versions of the CAPM remain linear but have an intercept term that is not equal to the risk-free rate and is referred to as the zero-Beta portfolio rate-of-return.

[5] If returns are not eliptically distributed, then one must assume quadratic utility functions in order that the CAPM obtain.

[6] Perfect markets imply the absence of frictions that impede investing. Thus, neither taxes nor transaction costs exist. Additionally, perfect markets imply that assets are infinitely divisible.

2. Models

$$\mathbf{E}(\widetilde{R}_i) - \mathbf{E}(\widetilde{R}_f) = \sum_{k=1}^{K} \beta_{ki} \{\mathbf{E}(\widetilde{R}_k) - \mathbf{E}(\widetilde{R}_f)\} \tag{3}$$

where K factors[7] are mapped onto a hyperplane. In the simplest case, the model has one factor, the market.

$$\mathbf{E}(\widetilde{R}_i) - \mathbf{E}(\widetilde{R}_f) = \alpha_i + \beta_{ik} \{\mathbf{E}(\widetilde{R}_k) - \mathbf{E}(\widetilde{R}_f)\} \tag{4}$$

This is referred to as the market model but should not be confused with the CAPM, which is an equilibrium model. Most factor models have several factors and are used to obtain a higher explanatory power than the market model. It is interesting to note that factor models do not inherently run against the grain of the CAPM. A careful reading of Sharpe's work and later commentaries indicates that any number of factors would be acceptable to him as long as they represent portions of the overall market risk and are systematic in nature. Sharpe later develops models with taxes, liquidity, dividend yields, etc.[8] and does not see theoretical inconsistencies therein with his original model[9]. For example, if the market were linearly decomposed into two components then the following relation would hold,

$$\mathbf{E}(\widetilde{R}_i) - \mathbf{E}(\widetilde{R}_f) = \left[\frac{COV(F_1, r_m)}{\sigma_M^2} b_{i1} + \frac{COV(F_2, r_m)}{\sigma_M^2} b_{i2}\right] \{\mathbf{E}(\widetilde{R}_k) - \mathbf{E}(\widetilde{R}_f)\} \tag{5}$$

For example, if F_1 referred to Gross National Product and F_2 to oil prices, but if both were linearly related to r_m, the market portfolio, then the CAPM would obtain because the market remains the unique source of risk, only having been compartmentalized.

3. Arbitrage Pricing Theory

Strongly resembling the multifactor model listed above, Steven Ross's Arbitage Pricing Theory (APT) has a similar conceptual framework as that of the CAPM but more flexible hypotheses:

- there exists an indeterminate number of systematic risks driving returns linearly
- investors perceive these risks and are aware of the security's sensitivity to these risks

[7] Formally, the models in this section contain expected values and are therefore not to be referred to as factor models, which are expressed in terms of observed returns and a concomitant error term.

[8] These include but are not limited to: "The Capital Asset Pricing Model: Traditional and 'Zero-Beta' Versions," Journal of the Midwest Finance Association, 1973, pp. 1-12; "Bank Capital Adequacy, Deposit Insurance, and Security Values Risk and Capital Adequacy in Commercial Banks, (Sherman J. Maisel, Editor), University of Chicago Press, 1981, pp. 187-202; "Some Factors in New York Stock Exchange Security Returns, 1931-1979," Journal of Portfolio Management, Summer 1982, pp. 5-19: "Optimal Funding and Asset Allocation Rules for Defined-Benefit Pension Plans", (with J. Michael Harrison), Financial Aspects of the United States Pension System , (Zvi Bodie and John B. Shoven, Editors), The University of Chicago Press (Chicago), 1983, pp. 91-105; "Factor models, CAPMs, and the APT," Journal of Portfolio Management, Fall 1984, pp. 21-25; "Practical Aspects of Portfolio Optimization," Improving the Investment Decision Process: Quantitative Assistance for the Practitioner and for the Firm, Dow-Jones Irwin (Homewood, Illinois), 1984, pp. 52-65.

[9] Not surprisingly perhaps, his academic rivals are not completely convinced.

- investors will actively lock in profits with expected risk arbitrage.

Ross's APT can be most aptly described as a factor model decomposing a vector random process into k common sources of randomness each with linear impact across assets[12]. Assuming a two-factor APT, for example, where each factor is designated as Θ, security return would be generated by the following,

$$R_i = \alpha_i + b_{i1}\Theta_1 + b_{i2}\Theta_2 + e_i \tag{6}$$

Like the CAPM, the APT stipulates that returns be linear in risk, however disagrees that the market beta must be the unique source of measured risk. The risk factors may also be variable in time. This model presumes that asset returns are described by a factor model and that a few "unobservable" sources of system-wide variation affect many other random variables which in turn affect the asset returns as a whole. The most important implication for the APT, is that if we live in multifactor world, then the average investor no longer holds the market portfolio because mean-variance optimization takes places on a multidimensional plane [11].

The generation of finance theorists inspired by Ross attempted to make observable that which was not via the route of factor analysis. Principal component analysis became an important dimension reduction technique developed to determine the underlying theoretical factors among a set of variables. Every test of the APT is actually a dual test of the APT and the fact that an approximate model can be tested by non-approximate[10] statistical tests.

Ross never attempts to specify the nature of the factors nor the number thereof. In this sense, the APT is untestable and impractical[11]. Notwithstanding this nonnegligible indictment to its credibility, empirical studies have been kind to the APT, showing that the "tangent" portfolio is less efficient in describing asset returns than a multifactor model that takes into consideration pervasive macro and micro risk. Roll & Ross (1980) specified five factors: the business cycle, interest rates, investor confidence, short-term inflation, and long-term inflationary expectations. Chen, Roll, and Ross (1986) amended the original factors which were reduced to four: rate of inflation (both expected and unexpected), spread between long-term and short-term interest rates, spread between low-grade and high-grade bonds, and growth rate in industrial production. Berry, Burmeister, and McElroy (1998) identify five factors, the first three coinciding with those of Chen, Roll, and Ross, and the other two being the aggregate sales in the economy and the rate of return on the S&P500.

The contribution of Fama & French also merits mention in this connection. One might say that the two bridged the gap between the theory and practice behind the APT by analyzing ratios used in the financial community and those circulating through the academic press and assigning them to risk factors[12]. Certainly, their efforts were a

[10] All factor models must face the errors-in-variables problem and this is not unique to the APT.

[11] One could also attack the CAPM on the same grounds, saying the market portfolio should include real estate and human labor, etc. rather than simply the S&P 500. In later works, Ross and Shanken attempt to specify the characteristics of acceptable portfolios from a mean-variance perspective but the issue of content is never fully addressed.

[12] Certainly Fama & French paid, and continue to pay, hommage to the CAPM in their work, but tended to add market risk as one among many in their design matrices. Antithetical to Sharpe's admission

welcome answer to the "data-mining" that resulted from the vagueness concerning the APT factors. For example, having noted that the book-to-market (B/M) ratio seemed useful in explaining the cross-section of equity returns, they developed the HML (High minus Low) factor which would refer to the premium paid by assets with a high B/M. Specifically, companies with this characteristic were called "value stocks" because their low market values indicated that they had lost value. A size factor was also developed named SMB (Small minus Big) which would describe the premium for the holding of small stocks. Small stocks paid extra premiums in good times to compensate owners for limited liquidity and lower chances of survival in difficult market situations. This matter will be developed upon later in this document.

4. Extended CAPM

For theoretically inclined CAPM adherants disgruntled by the empirical results, Merton's Intertemporal Capital Asset Pricing Model (1973) provided a ray of hope. For example a two factor model would take the following form:

$$\mathbf{E}(\widetilde{R}_i) - \mathbf{E}(\widetilde{R}_f) = \sigma_i \frac{(\rho_{iM} - \rho_{im}\rho_{Mm})}{\sigma_M(1-\rho^2 mM)}(\alpha_m - \mathbf{E}(\widetilde{R}_f)) + \sigma_i \frac{(\rho_{im} - \rho_{iM}\rho_{Mm})}{\sigma_m(1-\rho^2 mM)}(\alpha_m - \mathbf{E}(\widetilde{R}_f)) \tag{7}$$

where σ is standard deviation, ρ_{iM} refers to the coefficient of correlation between the asset and the market portfolio and ρ_{im}, ρ_{Mm} to that between the asset and the state variable and the market and the state variable, respectively.

5. Empirical Groundwork

The CAPM is not truly testable given the fact that expected returns are different from realized returns, expected risk-free is different from risk-free, accurate beta measurement is tedious, assigning a market proxy is difficult and once it has been assigned, forecasting its expected return and proving its mean-variance efficiency is even more of a challenge. To make matters worse, data is noisy and events such as crashes can lead to false conclusions for sideways and rising markets. That having been said, the CAPM has provided finance with a work-horse whose utility over the decades cannot be denied:

$$\mathbf{E}(\widetilde{R}_i) - \mathbf{E}(\widetilde{R}_f) = \beta_{pi}\{\mathbf{E}(\widetilde{R}_p) - \mathbf{E}(\widetilde{R}_f)\} \tag{8}$$

$$\widetilde{R}_{it} - \widetilde{R}_f = \alpha_{ip} + \beta_{ip}\{(\widetilde{R}_p) - (\widetilde{R}_f)\} \tag{9}$$

$\forall i = 1, ..., N$ and the first order condition in (8) combined with the OLS distributional assumption in (9) invokes the null-hypothesis of $H_0 : \alpha_{ip} = 0 \ \forall i = 1, ..., N$[13] [24]. Of course, a necessary prerequisite that is regularly overlooked is that the p portfolio is

that more than one factor could explain cross-sectional asset returns as long as the factors were market risk subcomponents correlated with the market Beta, Fama & French tended to orthogonalize their explanatory variables siding with the APT theory.

[13] The mutlivariate matrix form is

$$r = \mathbf{E}[r] + \mathbf{B}f + \epsilon \tag{10}$$

indeed one in the same as the M market portfolio when not in content, then at least in terms of mean-variance efficiency.

The following models represent the milestones of empirical research in this domain. These works were included to describe a sort of dialectic of risk premium analysis that has taken place over the past thirty years and to provide the reader with an understanding for the basis of the models described and tested in this work. The models are described in summary form, mentioning noteworthy sampling procedures, econometrical approaches, factor additions, tests and the concomitant results. Later in the document, the models will be revisited in a more discourse oriented format and compared with respect to content to that of the present study.

5.1. Black, Jensen, & Scholes (1972)[5], Scholes (1971)[35]. The first noteworthy tests of the CAPM[14] were conducted in the early 1970s. Black, Jensen & Scholes (1972) computed average monthly returns and portfolios sorted by Betas from a prior period. Subsequently a time-series regression was executed for an eight-year sample period. The equally weighted NYSE was used as the benchmark. Whereas 1931-39 showed a strong positive relation between risk and return, the relationship was smaller in 1939-47 and negative from 1957-65. Even more surprising, when the relationship was positive the empirical Beta was considerably flatter than expected: higher returns than the risk-free rate for the zero Beta portfolio and lower returns for the high Betas obtained. It was surmised that a missing systematic factor which was positively correlated to low Beta stocks ($\beta < 1$) and negatively correlated to high Beta stocks ($\beta > 1$). This missing factor was christened the "Beta factor" in light of these attributes and was econometrically expressed by Merton (1973) as

$$r_i - r_f = \beta_i(r_m - r_f) + \gamma_i(\alpha_o - r_f) \tag{11}$$

where α_o is the expected return on the zero-Beta portfolio, orthogonal to market returns by construction, with $\alpha_o > r_f$, $\gamma_i = \gamma_i(\beta_i), \gamma_i(1) = 0, and \frac{\partial \gamma_i}{\partial \beta_i} < 0$ [15]. This rationale is related to the APT and the gamut of multifactor models which ensued.

Fama & French (1993) used a similar time series approach, as does the author of this document, whereas Heston, Rouwenhorst & Wessels (1997) apply the cross-sectional regression methodology found in Fama & Macbeth (1973).

where n is the number of assets to be explained by the aforementioned common sources of randomness and f as a $k \times n$ matrix of random factors and $\mathbf{B}$ as a $1 \times k$ matrix of linear coefficients representing the assets' sensitivities to factor movements. Idiosyncratic returns are denoted by ϵ, which is a n-vector of asset-specific random variables. Furthermore, $\mathbf{E}[f] = 0$, $\mathbf{E}[\epsilon] = 0$, $\mathbf{E}[f\epsilon'] = 0$ and $\mathbf{B}$ is defined as a standard linear projection of conditional means, $\mathbf{B} = \mathbf{E}[(r - \mathbf{E}[r])f'](\mathbf{E}(ff'])^{-1}$. If we assume factors and idiosyncratic risk are uncorrelated, then the covariance matrix of asset returns, $\Sigma = \mathbf{E}[(r - \mathbf{E}[r])(r - \mathbf{E}[r]']$ can be decomposed into the sum of two matrices $\Sigma = \mathbf{B}\mathbf{E}[ff']\mathbf{B}' + \mathbf{V}$ where $\mathbf{V} = \mathbf{E}[\epsilon\epsilon']$, which is a diagonal matrix because we assume the idiosyncratic returns are uncorrelated with one another.

[14] The Sharpe & Cooper (1972) test was certainly noteworthy but conducted by a potentially biased experimenter. Average annual returns and betas were calculated for ten portfolios (NYSE equally weighted) sorted by beta values estimated from a preranking period of five years. A significant positive relationship obtained implying stability.

[15] Equation 15.36, 15.37a/b from Merton (1973) [30].

5.2. Fama & Macbeth (1973)[18]. Fama & Macbeth provided the first structured cross-sectional testing approach. Eugene Fama and James Macbeth aimed to test both the efficiency of capital markets and the justification for modern portfolio theory, that is, the formation of efficient portfolios by mean-variance optimizing investors. Cross-sectional regression estimates of returns vs. betas were obtained for 20 equally weighted portfolios of NYSE stocks sorted by beta values from a prior period (pre-ranking Betas). The benchmark portfolio was the equally weighted NYSE. They discovered that the empirical CAPM was flatter than the Sharpe-Lintner-Mossin CAPM. The model used included four factors, $\widetilde{R_{it}} = \widetilde{\gamma}_{0t} + \widetilde{\gamma}_{1t}\beta_t + \widetilde{\gamma}_{2t}\beta_t^2 + \widetilde{\gamma}_{3t}s_i + \widetilde{\eta}_{it}$. The empirical analog would test across twenty portfolios sorted on Beta

$$\widehat{R}_{pt} = \widehat{\gamma}_{0t} + \widehat{\gamma}_{1t}\beta_{p,t-1} + \widehat{\gamma}_{2t}\beta_{p,t-1}^2 + \widehat{\gamma}_{3t}\overline{s}_{p,t-1} + \eta_{pt} \tag{12}$$

where p=1, 2, ..., 20

Monthly NYSE stock returns from 1926-1968 were thereby regressed on post-ranking Beta, post-ranking Beta-squared, and a standard deviation proxy to test for the three principal empirical manifestations of mean-variance efficiency: the linearity of the expected risk and return relationship (E($\widetilde{\gamma}_{2t}$)=0) (C1), the absence of premium for non-market risk (E($\widetilde{\gamma}_{3t}$)=0) (C2), and market premium positivity E($\widehat{\gamma}_{1t}$)>0 (C3) [18]. The annex hypothesis of capital market efficiency would be demonstrated if $\widehat{\gamma}_{2t}$, $\widehat{\gamma}_{3t}$, $\widehat{\gamma}_{1t}$-$\left|\mathrm{E}(\widetilde{\mathrm{R}}_{\mathrm{mt}})\text{-}\mathrm{E}(\widetilde{\mathrm{R}}_{0\mathrm{t}})\right|$, $\widehat{\gamma}_{2t}$-E($\widetilde{\mathrm{R}}_{0\mathrm{t}}$) and $\widetilde{\eta}_{it}$ were fair games.

Perhaps more important than the results, was the unique methodology that surfaced as a result of this study that was aimed at reducing the statistical problems inherent to regression analysis. The error-in-variables[16] problematic was adressed and a cross-sectional regression was implemented across portfolios sorted for Beta. Hence, first the market model was run for all stocks on monthly returns and Betas were collected. Stocks were ranked and placed into portfolios to reduce the error-in-variables problem: if the errors in the estimated stock Betas are substantially less than perfectly correlated, the estimated portfolio Betas can be much more precise estimates of true Betas than those for individual securities. However, the forming of portfolios causes bunching of positive and negative sampling errors within portfolios, and to avoid the manifestation of this phenomenon, we form portfolios from ranked Betas computed from data for a given time period but then use a subsequent period to obtain the portfolio Beta estimates that are used to test the two-parameter model.

Hence, twenty portfolios were formed, eighteen of which contain int(N/20) and two contain $\frac{1}{2}$[N-20*int(N/20)] securities and if N is odd, the highest Beta portfolio gets an additional security. Over the next five years, Betas were recalculated once a year for the portfolios already ranked above (initial estimation period) and this was followed by a test period.

[16] Error-in-variables problems for linear fittings refers to the phenomenon whereby a "true" regression is $Y(i) = \alpha(i) + \beta(i)X(i) + \varepsilon(i)$ but data is limited to observations of $y(i)$ and $x(i)$ that are in fact estimates: $y(i) = Y(i) + u(i)$, $x(i) = X(i) + v(i)$. The least squares estimate of $b(i)$ in $y(i) = a(i) + b(i)x(i) + e(i)$ will be too low because of the additional error term in the denominator of $b(i) = \sigma_{y(i)x(i)}/\sigma^2_{x(i)} = \sigma_{Y(i)X(i)}/[\sigma^2_{X(i)} + \sigma^2_{v(i)}]$. On the other hand, $a(i)$ will be too high due to reduced $b(i)$ given that $a(i) = \overline{y}(i) - b(i)\overline{x}(i) = \overline{Y}(i) - b(i)\overline{X}(i) > \alpha(i) = \overline{Y}(i) - \beta(i)\overline{X}(i)$ if $\beta(i) > 0$ and $\overline{X}(i) > 0$.

C1, the linear risk and return relationship, and C2, the absence of premium for non-market risk could not be rejected, implying that market risk was compensated in returns positively and the possibility of non-linear or lagged non-market risk could not to be ruled out. This finding sowed the seeds to the subsequent Fama studies. C3, market premium positivity, was also accepted which coincided with the author's conclusion that mean-variance investor's hold the efficient market portfolio.

The significant evidence that expected returns increased with risk, was tempered by the fact that high Beta stocks had returns that were consistently lower than expected and low Beta stocks higher. It was assumed that the previously mentioned error-in-variables problem was present, and a brief discourse about the propriety of the benchmark portfolio was made.[17]

5.3. Fama & French (1992)[19]. Although a handful of studies had already been published to point out the deficiencies of the CAPM the first one to drive the point home to the wide-scale academic and financial community was that of Fama & French (1992)[18]. The study used the cross-section regression approach from Fama & MacBeth (1973). In this study, the authors looked at common ratios used by practitioners and in a first phase filtered them out for redundancy and then compared their explicative power with that of the CAPM. It was demonstrated that the predictive ability of lagged price and its derivatives, that is price-earnings, dividend-price, etc., could be made redundant by the inclusion of book-to-market and market size, and that these two factors had a greater predictive capacity than market risk.

First, a two-pass sorting taxonomy table was created to show that after having been controlled for size, Betas had no positive influence on returns. On the contrary the effect was negative. Then the following model was tested in a two-pass cross-sectional regression.

$$\begin{aligned} r_{it} - r_{ft} &= a_i + b_{i1}(r_{Mt} - r_{ft}) + b_{i2}\ln(size) + b_{i3}(E/P) + b_{i4}(leverage) + \\ & \quad b_{i5}(book - to - market) + e_{it} \end{aligned} \tag{13}$$

The results indicated clearly that market Beta was not significant and that is was rather size and book-to-market that were the key factors to explaining the returns of US stocks from 1963-1990[19].

Critics would later point out that the study was done over the 1970s after the oil shock and recession when many value stocks with their relatively low book-to-market ratios far outdid growth stocks. Others claimed size was none other than a proxy for an illiquidity premium which was destined to disappear as soon as large funds started purchasing the

[17] It stands to reason that mean-variance efficient "market" portfolios that had a higher risk than the theoretically true market portfolio of all investable assets would lead to a zero-beta portfolio with a superior expected rate than the risk-free rate.

[18] Other US based studies include Banz (1981) who made the case for size to explain the excess flatness of the empirical CAPM, Jegadeesh (1992) who demonstrated that Beta and size were in fact correlated and once this correlation effect was corrected for, Beta lost its explanatory power, Stattman (1980) and Rosenberg, Reid & Lanstein (1985) which showed the importance of the book-to-market ratio. Ball (1978) & Basu (1983) validated the significance of the price-earnings ratio, and DeBondt & Thaler vouched for the importance of the cash-flow-to-price ratio and sales growth.

[19] Other studies confirm this finding over the same time period.

small stocks to cash in on the apparant market inefficiency[20]. From an econometric point of the view, the study was also flawed for its use of OLS, when the coefficients were obviously company specific and–at least for the first pass–Zellner's Seemingly Unrelated Regression methodology should have been implemented. The methodology is therefore questionable but a flood of other documents nevertheless substantiate these findings.

5.4. Fama & French (1993)[20]. Fama & French developed a second model which looked at the previously elaborated firm specific factors, as potential proxies for global market factors. Although the work was entitled "Common Risk Factors in the Returns on Stocks and Bonds", and the additional asset classes of governent and corporate bonds were added to test the hypothesis of market integration via five-factor model including term and default risk, for the purpose at hand we will focus our attention on the three-factor equity model.[21]

The approach for model fitting was akin to that of the time-series regression implemented by Black, Jensen, and Scholes (1972). In addition to reasons related to asset-mixing nature of the work[22], the time-series approach permits the user to use t-statistics and the R-squared to investigate which mimicking factors adequately explain the cross-section of equity returns. Most important, the time-series allows the user to test the intercept term: well-specified model has a zero intercept. The model was presented as follows,

$$r_{it} - r_{ft} = a_i + b_{i1}(r_{Mt} - r_{ft}) + b_{i2}(SMB) + b_{i3}(HML) + e_{it} \tag{14}$$

where SMB, small-minus-big, refers to the premium obtained from investing in a synthetic portfolio which goes long small and short big stocks. The size premium is seen as an illiquidity premium for small companies with little turnover in their markets. HML, high-minus-low, refers to the premium obtained by going long high book-to-market and short low book-to-market ratio firms. It is a proxy for the premium earned from taking the extra risk of investing in firms which have recently been punished in the market for poor earnings or poor earnings forecasts. The market risk factor is included because the investor should be compensated for holding stocks that covary with the market and perform badly when the market and economy are doing badly.

In the second version of their model, one would argue, however, that the orthogonalization of the RM, RMO, implies the voracity of the APT and refutes the CAPM by construction,

$$r_{it} - r_{ft} = a_i + b_{i1}RMO_t + b_{i2}(SMB) + b_{i3}(HML) + e_{it} \tag{15}$$

[20] This would be consistent with the routine life and death patterns for anomalous risk premiums that are withered by arbitrage.

[21] Fama & French (1993) note that the term structure and default risk factors were highly correlated with the market risk.

[22] When testing across asset categories, the aforementioned factor loading approach has the advantage of easy interpretability as risk-factor sensitivities for both stocks and bonds. If one had attempted the cross-sectional approach, one would have encountered the problem of trying to assign equity specific factors such as size and book-to-market to bonds where their concrete relevance would have been questionable.

The authors find their factors to be statistically significant and the intercepts to be close to zero. Also noteworthy is the strong association observed between a stock's book-to-market ratio and its loading on the HML factor, leading one to the conclusion that the factor in question acts as hedge portfolio. That is, stocks with high B/M ratios have a positive factor loading whereas B/M low firms have negative HML loadings.

5.5. Heston, Rouwenhorst, & Wessels (1999)[28]. A recent study which applied the Fama & French (1992/3) methodology and concept of the firm characteristic inspired SMB systematic risk factor is that of Heston et al. (1997). The following model is fit in the context of pan-European integrated capital markets:

$$r_{it} - r_{ft} = a_i + b_{i1}(r_{Mt} - r_{ft}) + b_{i2}(r_{Mt-1} - r_{ft-1}) + b_{i3}(SMB) + e_{it} \tag{16}$$

The authors set out to specifically investigate the relationship between size and international market risk as exogenous variables for a cross-section of equities. Previous studies [Fama & French (1992), Jegadeesh (1992)] had shown that size and Beta coefficients were highly negatively correlated and that size filtration voided market risk of explanatory power. In contrast to the original specification of the Fama & Macbeth model, Heston et. al chose to disregard the market risk squared term and standard deviation of market model error, and rather concentrate on the Fama & French 1993 SMB[23].

Additionally, as is often the case, the lagged excess market return is embedded due to Beta measurement inaccuracy. After controlling for firm size and following the canonical methodology[20], the authors conclude size filtration does not prevent market covariance from being remunerated. In other words, both Beta and firm size are significant in explaining cross-sectional returns. This significance was limited to January, nonetheless. The Fama & French (1993) systematic size factor (SMB) was not relevant whereby it is implied that the F&F attempt to translate firm characteristics onto an axis of security risk premium hyperplane was unsuccessful. The study did not take on the issue of the HML factor, despite clear empirical evidence of its past importance[24].

This study contains a priori several conceptual incongruities. The Heston et al. study methodology clumped all European countries into one basket, despite DM strength in the early 1990s relative to its neighbors and the fact that the SMI and FTSE have imperfect correlations with the DAX. Heston et al. assume pan-European capital market integration, which is somewhat questionable given the length of the sample. Thus, the use of the DAX as the efficient market portfolio, the use of the German risk-free rate for excess return calculations, and the conversion of currencies into Deutschmarks all seem ambitious[25].

[23] The choice of factors was also surely dictated by the time-series approach, which lends itself to the inclusion of various risk factors.

[24] To the author's knowledge the Heston et al. study is unique in its approach of decomposing the pricing model which was designed to capture components of global market risk in its "clustered" format.

[25] Currencies were converted into DM and the DAX was used as the efficient market portfolio. It is well known that currency swings were quite volatile in Europe over the early 90s and these swings were attributable to speculators that played the DM-$ and $-£. Later the United Kingdom dropped out of the European Monetary Union. The use of the German risk-free rate to countries such as Italy and Greece imposes the strict Bundesbank anti-inflationary politics on countries with higher inflation and high interest rates and increases the risk of potential data smearing.

These factors and the existence of implicit currency pegs could have certainly distorted return correlations, leaving the Heston et al. results in a questionable light. Furthermore, the use of the SMB factor without mention of the HML factor and without testing the firm characteristics in the presence of the non-firm characteristic for redundancy leaves room for future studies and commentaries.

According to the criteria provided by Fama & Macbeth (1973), the Heston et al. study imply that European capital markets are not efficient (C2→E($\widetilde{\gamma}_{2t}$)=0 is rejected) and mean-variance optimizing investors do not hold the efficient market portfolio because they also optimize across the dimension of size. Size is seen as a potential proxy for other risk factors.

5.6. Lewellen (1999). Noteworthy conditional CAPM studies include Harvey (1991) and Jagannathan & Wang (1996). Jagannathan & Wang discovered that once the unconditional CAPM, with the same coefficients calculated for the entire period, was made conditional that the size effect disappeared. Lewellen investigates the ability of the book-to-market ratios to predict returns and interact with the Fama & French (1993) risk factors.

His interest for the ratio stems from past empirical studies documenting its apparant significance, which seemed to stem from the numerator controlling for size of expected cash flows and the denominator embedding discount rate information. Whence, the book-to-market ratio's explanatory power seems to derive from either distress compensation[26] or rather, exaggerated market swings–mispricing–occurring because irrational investors overreact in the presence of good or bad news, allowing for mean-reversion.

The study used time-varying composite factors to examine the credibility of the two rationales in the context of OLS and SURE time-series regressions. Lewellen's study can best be seen as a response, however, to Daniel & Titman (1997), who reject the Fama & French (1993) factor adaptation of the book-to-market firm characteristic, and provide evidence for the mean-reversion view of the ratio. The factor adaptation is refuted on the grounds that the loadings are correlated to firm characteristics. Sorting on B/M-h_i (the HML factor loading) yielded a stronger relation than in the factorized counterpart. This brings them to conclude that firm characteristics prevail in explanatory power over putative risk factors.

Lewellen's responds by testing whether a portfolio's B/M ratio predicts time-variation in expected returns and for interaction between B/M and the HML and SMB factors. To this purpose, a model was fit with time varying coefficients (conditional regression). SMB and HML were orthogonalized:

$$\begin{aligned} r_{it} - r_{ft} &= a_{i0} + a_{i,i}\ln(BE/ME_{t-1}) + [r_i + b_{i,i}\ln(BE/ME_{t-1})](RMO_t) + \\ & [s_i + b_{i,i+5}\ln(BE/ME_{t-1})(SMB_t) \\ & +[h_i + b_{i,i+10}\ln(BE/ME_{t-1}](HML_t) + e_{it} \end{aligned} \quad (17)$$

[26] A recent study, Akgun & Gibson (2001) shows that recovery risk plays an important role in the explanatory power of the book-to-market ratio.

The regressions demonstrate that HML and SMB absorbed significant variation in return risk and that B/M does not directly play a role in predicting expected returns, but does interact with the aforementioned risk factors. This implies the contrary of the Daniel & Titman firm-characteristic and overreaction hypothesis.[27] Lewellen specifically adresses Daniel & Titman by using non-biased HML with respect to industry portfolios demonstrating that HML is not significant only due to the factor correlation with certain industries that are currently out of favor with the investment public.

5.7. Harvey & Siddique (2000)[27]. SKS a.k.a. the skewness factor was introduced by these two authors who the previous year wrote "Autoregressive Conditional Skewness" (1999) in which conditional skewness and its impact on the persistence in conditional variance was analyzed[28]. The logic for the addition of the fourth factor was the repeated studies with three factors that were not able to eliminate pricing error, meaning that the three factors are not enough to explain the cross-section of returns–at least not in the United States. A fourth factor which yields a premium for the additional negative skewness that coincides with that of the market, or coskewness was proposed and corresponds to the partial derivative of asset skewness relative to that of the market:

$$\widehat{\beta}_{SKD_i} = \left(\frac{\mathbf{E}[\epsilon_{i,t+1}\epsilon^2_{M,t+1}]}{\sqrt{\mathbf{E}[\epsilon^2_{i,t+1}]}\mathbf{E}[\epsilon^2_{M,t+1}]} \right) \tag{18}$$

It is important to retain the difference between coskewness and skewness, $\frac{\mu(i)^3}{\sigma(i)^3}$. Negative skewness refers to the extra negative returns that remain once returns have been standardized by subtracting the mean and which are not compensated by positive returns of the same magnitude. Some markets are more negatively skewed that others. For example, markets that have a high degree of momentum–positive returns followed by relatively small positive returns–are prone to what seem to infrequent but large and negative drops. Assets with such properties would have to compensate investors through a premium, especially those assets which manifest this trait coincidentally with the overall market, whence we derive the notion of coskewness. One might wonder why this form of risk is not compensated through Beta, which is supposed to compensate investors for comovements with the market in poor states of nature. The answer lies in the fact that whereas the Beta compensates for comovements, the SKS woud compensate for the degree of the negative shock[29]. As such, we are dealing with a non-linear factor.

Adding SKS, we obtain the followed rendition of the four-factor model:

$$r_{it} - r_{ft} = a_i + b_{i1}(RM_t) + b_{i2}(SMB_t) + b_{i3}(HML_t) + b_{i4}(SKS_t) + e_{it} \tag{19}$$

Harvey & Siddique found significant correlations between the pricing errors of the three factor model and the S^- portfolios. Results indicated that book-to-market and size

[27] Lewellen also notes that it is inconsistent with the overreaction hypothesis that the factors explain returns unconditionally.

[28] SKS will be referred to later in the document, but is simply the premium from negatively skewed stocks with respect to positively skewed stocks.

[29] In laymen's terms, this could be seen as the "when-it-rains-it-pours" risk premium.

risk factors may to some extent proxy for conditional skewness. Specifically, portfolios which traditionally have a relatively high explanatory resistance to the three factor model, small size portfolios or momentum portfolios, experienced considerable improvement.

6. Testing for Switzerland, UK, and US over the 90's

Given a perusal of the aforementioned models and hoping to tackle the issue of data snooping, the author of the present document has chosen to apply an F&F 1993 style model to three countries with imperfect equity market correlations. Market integration for the three national entities in question was rejected so as to determine if each country displayed market efficiency and conformity to certain pricing models. Switzerland was selected because of its perceived trait as a safe-haven. The study is an indirect response to Heston et al. despite market selection disparity covering the UK and Switzerland and allowing comparison with the US.

Testing in various geographic locations is useful for rooting out data snooping and short term pricing anomalies. Every model fitting is in fact a joint test of market efficiency and the factors chosen. If anomalies exist over a short time frame, this suggests that a market ineffiicieny exists, especially if it disappears once the general public becomes aware of its presence. Persistent anomalies, on the other hand, would suggest that the model used was not appropriate and that a different design matrix needed to be implemented.

Coefficient results are often dependent on the time period in which they are tested. Certainly the most pertinent time-period to the current investor would be the present. Generally speaking, studies proving that the size and book-to-market ratio have greater explanatory power than market returns in explaining cross-sectional stock movements have been confined the US, where data is more abundant. International studies are therefore necessary to gain additional information and determine which phenomena apply to which geographic region[30]. Switzerland is an excellent example of a refuge country which for years has had stable asset returns.

6.1. Disposition of Study Constituents. Out of deference to the maxim "junk-in, junk-out", the author has attempted to carefully specify the thought process behind the analysis and the econometrical methodology. This provides a rational basis for a dialectical treatise of the matter at hand.

Operating Assumptions. At the various testing stages, one will have ample opportunity to refute the precepts of the CAPM and its offshoots, whence one should consider it fair to make at least one concession to the eventuality of market efficiency and functional pricing: price information is uniformly and freely available to all market participants. Further, although the hypothesis of market integration, both across geographical and asset class, might become more plausible in the not so distant future, it is currently best approached with skepsis. In light of this fact and given prior studies that suggest Switzerland's equity market warrants scrutiny [Fama & French (1998)], the following study makes

[30] Some market anomalies originate in the United States and then manifest themselves in other regions where they obtain for longer periods due to less efficient arbitrage.

the assumption of market segmentation, that is, that potentially different factors and almost certainly variant factor loadings explain the stock cross-section in geographically disparate regions. Whether this divergence has its origins in behavioral, preferential, or fiscal grounds will be discussed at a later point.

In contrast to Heston, Rouwenhorst, &Wessels (1997) who use the German DAX and European returns converted therein, and Fama & French (1998) who convert in US dollars and the US risk-free rate, the present study looks at each country separately with its own benchmark and risk-free rate. The risk-free proxy was the 3-month rate obtained from Thomson Datastream International.

Data. The aforementioned reasoning dictates the choices of the stock and index data in this study. S&P Compustat data was used for the stock data and benchmark indices were constructed from the market weightings thereof[31]. The author used the available stocks in the database whereby 432 US, 279 UK, and 46 Swiss stocks were analyzed. It is important to note that the MSCI index values were nonetheless used as the market due to robustness: Appendix I.

Most studies of this genre rely upon the guidelines set by Fama & Macbeth (1973) [leading to Fama & French (1992)] and or Black, Jensen, and Scholes (1972) (leading to Fama & French (1993)] so it useful to understand their justifications for data selection. Fama & French focus primarily on the US market and use a sample of all the non-financial stocks in the NYSE, AMEX, and Nasdaq from 1963-1990 listed by the Center for Research in Security Prices (CRSP), the income statement and balance sheet data of which were simultaneously maintained by COMPUSTAT. Financial firms were not included because these firms' high leverage ratios are not necessarily related to distress. The 1962 starting date was chosen because prior data was devoid of book-value and prices had a strong selection bias.

For their international study (1998), Fama & French continued using the NYSE, AMEX, and Nasdaq stocks for US data. Morgan Stanley's Capital International Perspectives data was used for non-US data. Countries were included which have at least ten firms possessing either book-to-market, earning-price, cash-flow-price or dividends-to-price ratios each December from 1974 to 1994[32]. MSCI data is noted for its treatment of the survivalship bias and the backfilling problem[33].

[31] Independently constructed MSCI indices partially adjusted to the criteria of free-float were tested for purposes of comparison but were not included in the document. The free-float has the advantage of not including treasury stock and certain forms of private placement and the weighting obtained are perhaps a better reflection of true equilibrium liquidity conditions. MSCI does not reveal the exact weightings of the component stocks so it seems that one is ineluctably obliged to confront this problem when using their data. Previous studies using MSCI data including Heston, Rouwenhorst, &Wessels (1997) and Fama & French (1998) did not have to deal with this issue and therefore relied upon the usual schema of market capitalized weightings.

[32] The fact that the same firms are not required to have data on all four ratios might be seen as a bit minimalist.

[33] Survivalship bias refers to the inclusion of only currently traded firms thereby ignoring information from companies that have disappeared. Backfilling is related to the survivalship bias and refers to the practice of adding historical data from newly added firms.

Using MSCI also has several disadvantages. Most MSCI firms are large, composing in aggregate approximately eighty percent of a market's invested wealth. It would therefore seem logical to compare MSCI indicies with the US S&P 500 rather than the NYSE, AMEX, and Nasdaq. Fama & French themselves comment in the discussion of their 1998 study, that a database of large stocks precludes meaningful tests for the size-effect based on Banz (1981) and Heston, Rouwenhorst, and Wessels (1995). Also, as in the case of COMPUSTAT, the availability and subsequent publication of accounting data is rather opaque. Having provided the reader with a comparative summary of data selection, the author affirms the use of Global S&P COMPUSTAT data with concomitant CRSP data for individual stocks and then using the corresponding market weighted index[34].

In order to deal effectively with delays in the apparition of accounting data, it is customary to lag them three to six months after the end of a fiscal year before inclusion and then maintain them until the next period's data is assumed available. In other words, fiscal (t-12) data is used beginning in March-June (t) and kept until March-June (t+1). This practice is based on the assumption that US companies file their 10-K reports to the SEC within 90 to 180 days of their fiscal year-ends. Fama & French started the practice of using 180 days based upon a study by Alfred, Jones, and Zmijewski (1992) which noted that more than 40% of firms with December fiscal year-ends do not comply with this date and file in mid-April along with their income taxes. Companies that do not have December often have September fiscal year ends. The present study assumes that this practice of filing with the income tax deadline still holds and efficient computer software and internet filing have made it simpler for companies to publish their accounting variables by April of (t).

Relative to Fama & French (1998), Heston, Rouwenhorst, & Wessels (1997) used a more robust sampling of firms using a total of 2,100 MSCI listed firms from 12 European countries between 1978-1995: Austria (60), Belgium (127), Denmark (60), France (427), Germany (228), Italy (223), The Netherlands (101), Norway (71), Spain (111), Sweden (134), Switzerland (154), and the UK (494). The larger selection of firms would not exempt Heston et al. from the charge that the MSCI tracked firms are relatively large given that 60 to 90 percent of each country's market capital is included.

Preliminaries. Switzerland presents itself as a somewhat special case and merits discussion. Haag (1997) studies exclusively the Swiss market tracking 423 issuances from 259 companies tracked by Datastream International. The index was corrected for survival bias.[35] Switzerland is unique in its diversity of stock listing types: registered (Namenaktien), bearer (Inhaberaktien), participation certificates (Partizipationsscheine), and profit sharing certificates (Genussscheine)[36]. None of these various classes of shares are considered legally to be preferred and would not necessarily have a different pay-out protocol

[34] The theoretical market portfolio should represent the aggregate of assets and be capable of representing market clearing supply and demand conditions. Equilibrium pricing can only take place once markets have cleared. From this vantage point and assuming we accept the potentially inaccurate market portfolio, the free-float weights are perhaps more representative of the conditional weightings of the securities. Free-floats were selected by MSCI as the preferred weighting protocol to be implemented by the end of 2002.

[35] It is not clear if the backfilling issue is addressed.

[36] Although most of our attention goes to selecting appropriate market values, the book-values of Swiss stocks are calculated with respect to dividend ratio. For example, if the bearer stock had a Fr. 20, the registered a Fr. 5, the participation certificate Fr.1, and the profit sharing certificate Fr. 1 dividend then

in the event of default. To obtain a book-to-market equity value that reflected these various classes of market equity, Haag weights the different issues according to their market capitalizations.

Despite this attempt at accuracy, the Haag approach is not without its disadvantages, especially with regard to international comparability. In the US and UK only common (ordinary) equity shares are evaluated in the course of most studies for the BE/ME ratio (B/M). Book equity refers to the facial value of the equity at time of issue, whereas Market Equity is simply the current price of shares times number of shares outstanding. COMPUSTAT code CEQ is mnemonic representing book common equity used by the present study and, to the best of the author's knowledge, all past studies. SEQ differs from CEQ in that it is the book value of total shareholders' funds. The latter would obviously include various classes of preferred shares, tracking stocks, and even company issued Global Depositary Receipt (GDR). In order for the Swiss stocks to stand on the same footing as their foreign counterparts, the author opts for the CEQ/MKVALI ratio for the registered stock where MKVALI refers to the market value at the issue level (MKVAL would have included quotes for all issues), given the fact that this is the correct ratio for the US and UK firms. In other words, it would have been improper to use SEQ/MKVAL uniquely for Switzerland, because comparison of results on an international basis would have no longer been possible.

The choice of CEQ/MKVALI has the additional non-negligible advantage of providing more interesting results from an econometric point of view. One is less interested in the level of the market value than in its covariance with other factors, especially because the other factors are composed of the stocks themselves and smearing its comovements would have been suboptimal on several levels, as we will later see. Given the choice of using one issue, one is faced with the question of which[37]. Bearer shares are theoretically more liquid than registered, but registered shares have longer time series. Participation certificates do not give voting privileges. Profit sharing certificates are often given to employees at certain times of the year. The present study relies on nominal share data for Switzerland, but uses bearer when the former is not available. The liquidity of nominal shares ensures that share prices accurately reflect the collectivity of investor opinion about the discounted value of expected stock dividends. Efficient price information means that covariances analysis can lead to meaningful results. On the other hand, adding low liquidity issues to high liquidity counterparts might seem technically correct, but leads almost certainly to lagged informational apparition and significant autocorrelation.

Further, in addition to smearing important covariance data, a dampening effect would present itself during any merger and acquisition activity. These events manifest a market increase in the value of the voting stock (bearer and nominal) relative to the non-voting stock (participation certificates). Finally, the relatively short time span was necessary

the following relations hold. The registered share has book-value ratio of one-fourth that of the bearer share and 5 times that of the participation and profit sharing certificate. Likewise, a bearer stock counts four times as much as a registered share and the certificates one-fifth the registered. So if there are 100,000 bearer, 200,000 registered, 1 million participation certificates, and 500,000 profit-sharing certificates then the respective registered share book-value would be weighted by the following denominator: [(4*100,000) + 200,000 + (1,000,000/5)+(500,000)/5]=900,000.

[37] Isakov (1995) shows that the choice of Swiss registered or bearer stocks yield statistically similar results for his CAPM study.

so that enough stocks in Switzerland had data to permit four-by-four two-dimensional taxonomy tables and have at least ten stocks in each of the bins.

Methodology.

Base Taxonomy: Two Pass Sorting. Appendix I includes a summary of the country returns with variance and correlation since January 1995. The MSCI index returns and histograms indicate that X relative to the S&P Compustat market weighted benchmark.

A two-dimensional taxonomy of the size/book-to-market and size/Beta portfolios is useful. The study focuses on the last ten years and begins with December 1992. This was specifically done to put Switzerland on an equal footing in terms of having enough stocks to provide with a minimal number of stocks for the 16 size-B/M or size-Beta bins.

Portfolios are ranked and sorted in April of each year, meaning returns for each selection start in May and go until April of the next year. Every year, new returns go into the vector. The first dimension is always size; once portfolios are sorted into four size bins in April of year (t), they are then sorted based on B/M from December (t-1) into four more size portfolios. Negative B/Ms are rejected. To be included stocks need to have a B/M from December (t-1). Once stocks are sorted into their bins, we collect the value weighted (not equally weighted) monthly returns on each of the 16 portfolios from May (t) to December (t+103), which corresponds to temporal sample period running from April 1993 to December 2001. Each bin gets a [103,1] vector and its time series average is entered in Appendix III(a).

Size is next sorted on pre-ranking Betas which are estimated as the sum of the slopes on market return and lagged market return in the regression:

$$(P_t - P_{t-1})/P_t = b1 + b2(R_{m(t)} - R_{f(t)}) + b3(R_{m(t-1)} - R_{f(t-1)}) \tag{20}$$

Every year stocks are re-ranked in terms of size and Beta coefficients and portfolios are reformed. Portfolio returns over the subsequent year are collected per month, even though one only enters the time series average in the table. That is, stocks are re-ranked on size and Beta, then we collect returns from t (May 1993) to t+11 (April 1994) and the first 12 returns in a [103,1] vector. Subsequently t+12 (May 1994) to t+23 (April 1995), etc. are collected until December 2001. The return vector constructed in this manner yields the value for each of the 16 size-Beta portfolios: Appendix III(b).

Two stability tests are effectuated for Beta and size. Post-ranking Beta refers to the Beta measure assigned to bins and the corresponding stocks. The values are calculated by obtaining the full-sample post-ranking return vector for each bin and then regressing that on the market portfolio using equation (20). Naturally, the original bin formation that yields the necessary returns derives from pre-ranking Betas. Subsequent testing will be based on the post-ranking Beta because it is deemed more accurate due to errors making individual stock Beta non-reliable Appendix III(c). An accurate analysis mandates that pre-ranking Betas increase concomitant to their post-ranking counterparts.

The final taxonomy table determines size stability and is constructed by sorting post-ranking size on the axes of pre-ranking size and Beta.. The average size of a portfolio is the time-series average (the average across the [103,1] vector) of monthly averages of ln(ME) for stocks in the portfolio formed as described above in the pre-ranking Beta section. ME is denominated in millions of dollars.

The three countries in question manifest mixed results for the size, beta, or B/M effect. USA monthly returns sorted by size and B/M show that after controlling for size a higher B/M tends to slightly reduce rather than increase return with the exception of the highest B/M bin. High B/M, as well recall, suggests the company has been oversold by investors or is in the midst of financial distress, or both. Given the boom cycle prevalent in the United States over the 90s, it is not a surprise that such companies remained afloat and eventually remunerated investors with somewhat higher returns for the incurred risk. Pre-ranking Beta sorting yields no meaningful results. Post-ranking Betas tend to converge towards zero consistent with the results of Blume (1975). Size/Pre-ranking Beta sortings indicate that companies with higher betas grew over time. Especially in the small size bins, low unconditional skewness was.rewarded with a relative premium. Further, the small and medium bins confirmed with conditional skewness effect with lower premiums for higher positive values.

The UK shows little conclusive evidence of any "effect" with the exception of skewness and coskewness where low skewness warrants a premium over desired positive skewness.

Switzerland confirms the Size/Pre-Beta Sorting effect previously seen in the United States over the period in question, suggesting that companies with initially higher betas went on to larger growth in market capitalizations. Although non-conclusive with respective trends across bins, the Swiss portfolios once again show that negative premium was associated with the holding of positively skewed portfolios.

Creation of Synthetic Factors: SMB, HML, RMO, and SKS. Consistent with the methodology presented by Fama & French (1993), synthetic factors in the form of long/short portfolios are created and the returns market weighted. The two canonical synthetic factors are the previously described SMB and HML, and the third to be considered is SKS, or skewness, based upon Harvey & Siddique (2000). Every year stocks are re-ranked on the critereria necessary for the creation of the these factors. The ranking occurs in April rather in June, the traditional ranking month. This was done for two reasons, including the fact that previous studies indicate that 10-K forms in the US are regularly submitted along with tax forms for the April 15th deadline and the fact that using April accords the author an extra couple of months to register potentially anomalous behavior.

Whereas in the previous taxonomy section we sorted once per year and later collected monthly data, in this portion of the study we are obliged to rank and sort and collect returns on a monthly basis. Each month, all stocks with market values for the previous month and book value data for December of the previous fiscal year are ranked and sorted independently on size and B/M[38]. Fiscal data used for the numerator, as previously

[38] Although the models will be fit with ln(BE/ME) and ln(ME) ranking and weighting is done in non-logarithmic format.

detailed, refer to the past December data prior to data collection. The numerator remains the same for the entire year. The denominator is market based and corresponds to the month of collection. Every time stocks get ranked, their returns for that month are weighted by market capitalization, and these returns go into the appropiate portfolios making up the synthetic factors.

The factors to be used include SMB, HML, RM, RMO, and SKS. SMB and HML have already been elaborated upon in the Fama & French (1993) model description. RM is simply the market factor; RMO is the orthogonalized RM, the excess market risk, which is obtained by regressing RM on SMB and HML [(Rm-Risk Free) = beta0 + Beta1(SMB) + Beta2(HML) + error] and then adding the beta0 vector to the error vector. SKS is the coskewness factor. Important details will be dealt with below.

For the creation of the SMB and HML factors, the first step is to sort stocks each month into two size portfolios using the median market value: S (small) and B (big). At the same time, stocks are sorted into three B/M portfolios, using as breakpoints the 30th and 70th book-to-market percentiles and excluding negative values: H (high), M (medium), L (low). Portfolios are created from the intersection of the two size and three B/M portfolios: S/L, S/M, S/H, B/L, B/M, B/H, where for example, S/L contains stocks in the small ME group with low book-to-market ratios. Weighted monthly returns are calculated for each of the six portfolios.

SMB equals the difference in returns between the matching size portfolios, holding the corresponding B/M constant divided by three (to get the average): [(S/L-B/L) + (S/M-B/M) + (S/H-B/H)]/3. HML refers to the difference in returns between the two matching B/M portfolios, holding corresponding Size constant divided by two to get the average: [(S/H-S/L) + (B/H-B/L)]/2. Appendix IV includes synthetic factor statistics and correlations.

In order to investigate coskewness, two value weighted hedge portfolios that capture this effect are created and named SKS. A prerequisite for SKS creation is the collection of portfolios negatively and positively skewed with the market. This is done by regressing the asset on the orthoganalized square of the market returns, and taking the residuals for those months are then used to construct beta SKD . Portfolios are then ranked on the basis of past coskewness and the top 30 percent goes into the creation of the high coskewness portfolio whose market weighted returns are calculated. The low coskewness portfolio is then calculated as per above and the respective returns are subtracted. Due to the small sample, rather than using only subsequent returns, the entire sample is used which has the added benefit of synchronizing to the other factors.

Econometrical Considerations. OLS with correction for heteroskedasticity was used for the models with risk premium based factors whereas Arnold Zellner's technique for "Seemingly Unrelated Regressions" (SURE) was used later on in the presence of the firm specific factors. In 1962 Zellner proposed this efficient method for the estimation of seemingly unrelated regressions and testing for aggregation bias, whereby Aitken's generalized least-squares is applied to the entire system of equations. Empirical studies demonstrated that from the perspective of asymptotic efficience, it was better to stack the equations accordingly than use an equation-by-equation OLS approach. The gain in efficiency is especially large when the disturbance terms in the various equations are highly correlated and the design matrix variables are not.

Practically speaking, the quintessance of SURE is the use of equation-by-equation OLS residuals $b = (X'X)^{-1}X'y$, $e = y - X'b$, knowing that $\widehat{\sigma}_{ij} = \frac{1}{T}\widehat{e}_i'\widehat{e}_j = \frac{1}{T}\Sigma_{t=1}^{T}\widehat{e}_{it}'\widehat{e}_{jt}$ for the estimation of a covariance matrix which enables the construction of Aitken's estimators. Whence, via ee' we obtain the Σ error covariance matrix[39] and subsequently,

$$\widehat{\beta} = (X'(\Sigma^{-1} \otimes I_T)X)^{-1}X'(\Sigma^{-1} \otimes I_T)y \tag{21}$$

$$(y - X\beta)'(\Sigma^{-1} \otimes I)(y - X\beta) \tag{22}$$

subject to linear restrictions $R\beta = r$, given by $\widehat{\beta}^* = \widehat{\beta} + CR'(RCR')^{-1}(r - R\widehat{\beta})$ where $C = [X'(\Sigma^{-1} \otimes I)X]^{-1}$ and $\widehat{\beta} = CX'(\Sigma^{-1} \otimes I)y$. $H_0 : R\beta = r$ and thus against the alternative $H_1 : R\beta \neq r$ in which case the $R\widehat{\beta} \sim N(r, RCR')$ relation no longer holds.

The generalized Wald test is appropriate for coefficient testing for SURE given the replacement of unknown Σ with $\widehat{\Sigma}$: $\widehat{g} = (R\widehat{\widehat{\beta}} - r)'(RCR')^{-1}(R\widehat{\widehat{\beta}} - r) \xrightarrow{d} \chi^2_{(J)}$[40] which only holds when H_0 is true.

Although the Shanken F-Test [24] is not appropriate for SURE testing, an extended version of the single-equation F-test is acceptable. Assuming normal distributions,

$$\lambda_F = \frac{\widehat{g}/J}{(y - X\widehat{\widehat{\beta}})'(\widehat{\Sigma}^{-1} \otimes I)(y - X\widehat{\widehat{\beta}})/(MT - K)} \approx \widehat{\lambda}_F = \frac{\widehat{g}}{J} \sim F_{(J, MT-K)} \tag{23}$$

where J refers to the number of coefficients tested, M the number of sample subsets, and K the number of factors. Having delineated the SURE procedure which will provide for efficient results from which more information regarding the signfiicance of the coefficients, we move on to the model fitting.

The significance of coefficients is determined with a normal F-Test. The a_i coefficients are tested for the entire group in question–either size or B/M sorting–with the Shanken F-Test: GRS=$\frac{T-N-K}{N}[1 + \widehat{\mu}_K'\widehat{\Omega}^{-1}\widehat{\mu}_K]\widehat{a}'\widehat{\Sigma}^{-1}\widehat{a}$ where

$\widehat{\mu}_K$	vector of returns for the K factors
$\widehat{\Omega}$	variance-covariance matrix of the K factors
$\widehat{\Sigma}$	estimate of the covariance matrix of $\widehat{a}$
N	the number of $_i$ portfolios
K	the number of indepedent variables including $\widehat{a}$

GRS is significantly different than zero is we reject GRS$\sim$ $F(df(N)$, T-N-K).

[39] $ee' = \Sigma$ and most computer programs use an iterative procedure based on $\widehat{\widehat{\sigma}}_{ij} = T^{-1}(y_i - X_i'\widehat{\widehat{\beta}}_i)'(y_j - X_j'\widehat{\widehat{\beta}}_j)$ where $\widehat{\widehat{\beta}}' = (\widehat{\widehat{\beta}}_1', \widehat{\widehat{\beta}}_2', ..., \widehat{\widehat{\beta}}_M')$, which can be used to form new β estimators until convergence.

[40] The coefficient testing statistic, can also be written as a sum of squares, noting that $\widehat{g} = (R\widehat{\widehat{\beta}} - r)'(RCR')^{-1}(R\widehat{\widehat{\beta}} - r) = (y - X\widehat{\widehat{\beta}}^*)'(\widehat{\Sigma}^{-1} \otimes I)(y - X\widehat{\widehat{\beta}}^*) - (y - X\widehat{\widehat{\beta}})'(\widehat{\Sigma}^{-1} \otimes I)(y - X\widehat{\widehat{\beta}})$ where $\widehat{\widehat{\beta}}^*$ refers to the restricted seemingly unrelated regression estimator.

7. MODEL FITTING

Appendix I describes the characteristics of the market portfolio for the three countries in question. The S&P Compustat composite portfolio was selected over the MSCI due to more pronounced levels of skewness which will potentially underline latent premiums. The USA has a monthly standard deviation of 0.042 with a 0.082 skewness, the UK and Switzerland with respective values of 0.04 and 0.02, 0.051 and 0.05. Several models considered "canonical" were tested and evaluated with respect to RMSE[41] and Generalized Wald-Chi Squared test across the stacked size or B/M sortings' constant values.

7.1. 1. Market Model.

$$r_{it} - r_{ft} = a_i + b_{i1}(r_{mt} - r_{ft})^{42} + e_{it} \tag{24}$$

7.2. 2. Harvey & Siddique conditional skewness SKS.

$$r_{it} - r_{ft} = a_i + b_{i1}(RM_t) + b_{i2}(SKS_t) + e_{it} \tag{25}$$

7.3. 3. Harvey & Siddique conditional skewness SMINI.

$$r_{it} - r_{ft} = a_i + b_{i1}(RM_t) + b_{i2}(SMINI_t) + e_{it} \tag{26}$$

7.4. 4. Fama & French (1993) Three Factor.

$$r_{it} - r_{ft} = a_i + b_{i1}(r_{mt} - r_{ft}) + b_{i2}(SMB_t) + b_{i3}(HML_t) + e_{it} \tag{27}$$

7.5. 5. Three-Factors with Orthogonalization.

$$r_{it} - r_{ft} = a_i + b_{i1}(RMO_t) + b_{i2}(SMB_t) + b_{i3}(HML_t) + e_{it} \tag{28}$$

7.6. 6. Four-Factors with Stress on conditional skewness .

$$r_{it} - r_{ft} = a_i + b_{i1}(RMO_t) + b_{i2}(SMB_t) + b_{i3}(HML_t) + b_{i4}(SKS_t) + e_{it} \tag{29}$$

7.7. 7. Five-Factors with Stress on conditional skewness .

$$r_{it} - r_{ft} = a_i + b_{i1}(RMO_t) + b_{i2}(SMB_t) + b_{i3}(HML_t) + b_{i4}(SKS_t) + b_{i5}(SMINI_t) + e_{it} \tag{30}$$

[41] RMSE=$\sqrt{\frac{1}{T}\sum_{t=1}^{T} e_{t+h,t}^2}$.

[42] The period specific risk-free rate has been subtracted to obtain the pertinent factors, unless mention to the contrary. Thus RM_t=$r_{mt} - r_{ft}$, etc.

7.8. Discussion. Consistent with the formation of the previously described size and B/M ratio portfolios, results were analyzed first for the separate bins and subsequently across bins for the Wald tests and the LSUR procedure In the former, it was often the author's practice to search for trends or noteworthy results. B/M sorting and bin formation did not lead to interesting results in the three countries studied. The author concludes that over the last decade, portfolio managers using either Beta or B/M to construct strategies did so more out of superstition than fact. Below, the country specific observations:

USA. The first surprise the reader is likely to encounter comes in Appendix V where the US factor correlations with the MSCI portfolios are to be found. The synthetic S&P Compustat Aggregate are not used in the evaluations for Appendix X-XIII. The market displays weak negative with SMB, HML, SKS, and strong positive correlation with SMINI. This would suggest that as the market rose over the past decade, holders of small stocks with high book-to-market equity ratios were not paid for the supposed extra risk they were taking: big stocks got bigger and companies with poor B/M ratios did not experience mean reversion. Indeed this was the case in the decade of momentum.

Across size sorted portfolios, the RMSEs tend to drop off, that is, to improve from model 1 to model 5 (the Fama & French 3-Factor model), where it reaches its lowest point. The Campbell & Siddique conditional skewness SMINI model also showed low errors. It was interesting to note that across the countries studied, model 1, the simple CAPM, did well in explaining the results for middle sized firms (S3), model 2, explained high B/M ratio firms (B5), model 3 explained B2 firms, model 4 explained S4, model 6 B3, and model 7 large S5 firms the best. These results were confirmed by the Adjusted R-Squared, Akaike Information Criterion and even the Schwarz information criterion, which is known for its penalization of extra non-significant factors.

The B/M sortings seem less efficient and less conclusive. The intercepts are significantly non-zero but the Wald-Chi Square statistics indicate that model 1 (the market model), model 3 (Campbell & Siddique conditional skewness SMINI) and model 5 have least significant values, which suggests the model factors explained returns more efficiently.

Appendix XI indicates that most of the selected factors had significant coefficients. For model 1, we observe that the beta t-statistic increased in size. Model 2, the Campbell & Siddique SKS factor added to the CAPM, both alpha and beta become more signficant in size. Model 3, the CAPM with SMINI displays S3 with an unusually low Beta of 0,42 and B2 with 0.363. In both cases, the coefficients are significant. The presence of SKS forces the Beta to alter its role. Model 4, the canonical Fama & French model, manifests–as expected–an S5 with a negative SMB coefficient and only S2 and S3 have positive HMLs, but they are insignificant. At both size extremes, S1 and S5, asset holders are paying a Book-to-Market ratio premium, and this trend is also present in the B/M sorting. Model 7, where Fama & French (1993) hosted the Harvey & Siddique (2000) SKS and SMINI factors had B1 and B3 bins with negative Betas, although the B3 coefficient was non-signficant.

One can stress the importance of the results in the previous paragraph via Appendix X where Wald-Chi Square tests were performed on the five size portfolios simultaneously for each model. The purpose was to see whether the model's alpha–unexplained but non-random return–was least pronounced in the case of model 1 and highest for model 6. The B/M sorting had model 2 and 3 as those producing minimal alpha.

Model 6 with orthogonalized RM (RMO) is surprising given Betas reduced to nullity for S2, S3, S5, B1, B3, B4 portfolios which is inconsistent with results from Fama & French (1993). Akin to the model, the presence of SKS, the premium for most negatively skewed stocks minus that for the most positive, forces dramatic changes upon the explanatory power of the MSCI market portfolio.

UK. The Appendix V correlation tables show that the UK had a negatively correlated RM with SMB, as in the case of the US where the trade-off between size and beta were also evident, but others factors were positively correlated, suggesting mean-reversion for high B/M firms. The UK had similar results to those produced by the USA, also yielding the lowest RMSEs to the Fama & French 3-Factor model The B/M sortings yielded different results but, as previously mentioned, seem to offer the practioner a lower degree of reliability. Model 3, 5, and 7 have the lowest Wald Chi-Square statistics.

Appendix XI indicate that the UK had lower Betas than the US, especially the case for model 3, where B1 and B2–low book-to-market equity firms, that is, momentum picks, had significantly negative values. HML coefficients for models 4 and 5 are generally positive for the UK whereas negative for the US, indicating the prevalence of mean-reversion or remuneration for the holding of firms with low prices relative to book-value in the UK. Model 7, like the US, renders RMO Betas null. Another commonality: both countries have positive model 6 SKS coefficients and this inverts in the presence of the Model 7 SMINI. Apparently the pure negative skewness premium forces the differenced negative and positive skewness premium into a different role.

Appnedix X shows that model 3 and model 7 had the least alpha for the size sort, whereby B/M sort pointed towards model 2 and 3, perhaps a coincidence with the US portfolios that CAPM with SKS and SMINI modifications would best explain middle B/M ratio firms.

Switzerland. Similar to the UK, size-beta trade-off present with B/M mean-reversion. The Fama & French 3-Factor model once again had the lowest RMSE across portfolios. Switzerland is the only country with stastically zero-intercepts for size portfolios across model 1 (the simple CAPM), model 3, model 5, and model 7, which indicates that in the 90s the market was theoretically efficiently priced with respect to one of the four conventions. The B/M portfolios show similar results for intercepts for model 2 (Harvey & Campbell conditional skewness SKS), model 3, model 4 (Fama & French (1993) Three Factor without orthogonalization).

Appendix X shows similar patterns as the US and UK for the B/M bins, with size sort leaving it difficult to choose between model 1, 3, 5, and 7. Appendix XI joins Switzerland with the UK with respect to the relatively low Betas (between 0.60 and 0.80). Model

3 has a large SMINI premium relative to the US but comparable to the UK. Model 4 has large HML coefficients relative to the other countries tested. Model 6 and 7 confirm observations made above.

This results is perhaps best explained by the large concentration of the market in several extremely large capitalized companies and the fact that S&P Compustat data for B/M allowed the author only 10-20 companies per bin over the ten year period.

7.9. 8. Conditional Three-Factor with B/M Interaction.

$$\begin{aligned} r_{it} - r_{ft} &= a_{i0} + a_{i,i}\ln(BE/ME_{t-1}) + [r_i + b_{i,i}\ln(BE/ME_{t-1})](RMO_t) + \\ &\quad [s_i + b_{i,i+5}\ln(BE/ME_{t-1})(SMB_t) \\ &\quad +[h_i + b_{i,i+10}\ln(BE/ME_{t-1}](HML_t) + e_{it} \end{aligned} \tag{31}$$

7.10. 9. Conditional Three-Factor with B/M Interaction. This model uses the $SKEW_{t-1}$ term which refers to skewness calculated at $(t-1)$ over the previous six months. Consistent with the notion of systematic risk, this coefficient should not be significant. Significance thereof would imply the relevance of a characteristic based model.

$$\begin{aligned} r_{it} - r_{ft} &= a_{i0} + a_i(SKEW_{t-1}) + [r_{i0} + b_{i,i}SKEW_{t-1}](RMO_t) + \\ &\quad [s_i + b_{i,i+5}SKEW_{t-1}](SMB_t) \\ &\quad +[h_i + b_{i,i+10}SKEW_{t-1}](HML_t) + e_{it} \end{aligned} \tag{32}$$

7.11. Discussion. Consistent with the aformentioned ”canonical models” results, the RMO, SMB, and HML factors were repeatedly the most significant. The B/M factors only obtained (on a regular basis) when coupled with a signficant global factors. Switzerland was unique in the fact that the skewness firm characteristic assumed an important explanatory role. In contrast to Lewellen (2000), the author finds that the B/M firm characteristic offers minimal information about next period return.

8. CONCLUSION

Capital markets are certainly not always as efficient as theorists intend them to be. It seems likely that at any given time there are free-lunches to be made for those looking in the right places. The CAPM theoretical construct suggests that investors are remunerated as a function of systematic risk. The present study indicates that an orthoganlized version of this factors is indeed remunerated internationally. The SMB and HML factors are country specific "market" factors referring to the size and book-to-market proxies. The size factor could actually be a liquidity premium or remuneration for "irresistance to market volatility", whereas the global HML factor could have behavioral origins suggesting that market participants exaggerate and "overexprapolate". Long term, these two factors in addition to the market–which could incidentally be seen as subcomponents of the market (see equation [5]) are indeed remunerated and do not seem to represent short-term market anomalies. This study thereby confirms the work of Fama & French in this domain and shows that even with the addition of the B/M characteristic that the factors remain significant.

Skewness and Coskewness have mixed results, just as in Harvey & Siddique (2000). The present work concludes that the SMINI–negatively coskewed stock premium minus the risk-free rat–is a better measure than SKS–negatively coskewed stock premium minus postively coskewed stock premium.

Especially Switzerland, the home of the "prudent" investor show significant coefficients for SMINI and zero intercepts which aligns well with the theory about risk aversion, which stipulates that risk averse individuals should demand more for stocks with tendentially negative conditional skewness . The results indicate that the Swiss do not live in a normal, mean-variance universe.

Extensions for future studies include the momentum effect premium and the put/call premium ratio, which might include additional information about future skewness and coskewness rather than only the past. Further, given the uniqueness of the 90s boom, the aforementioned premises should be analyzed across other time periods.

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9. APPENDIX I: MARKET CHARACTERISTICS

9.1. USA.

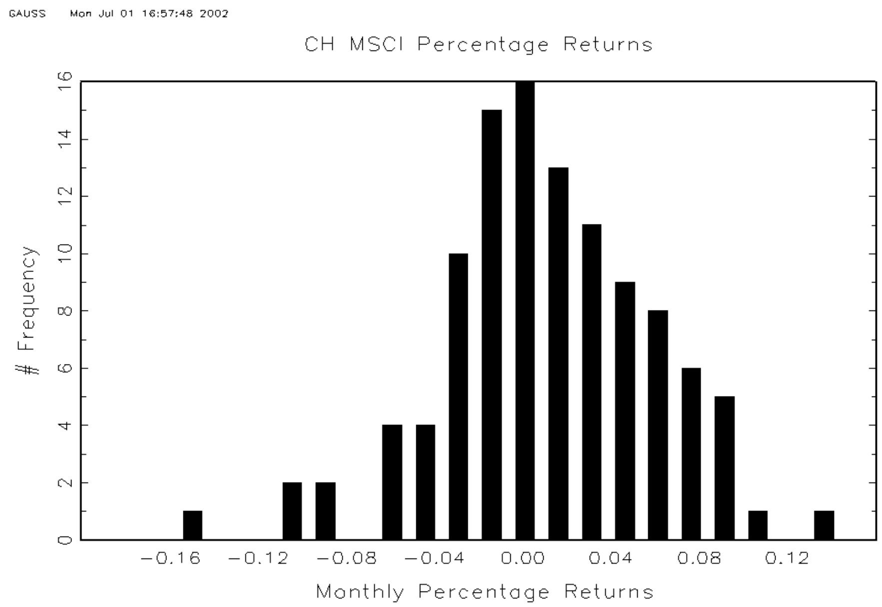
Index	Median n	Avg.ROR	Std.Dev.	Skewness	Avg Size
S&P Compustat USA	432	0.018	0.042	0.082	14872
MSCI USA	.	0.010	0.042	0.013	.

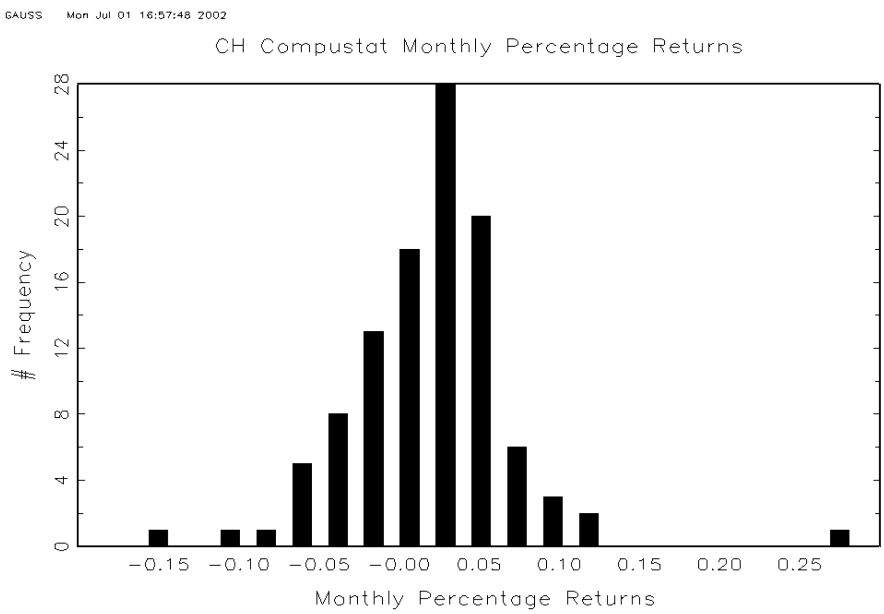
9.2. UK.

Index	Median n	Avg.ROR	Std.Dev.	Skewness	Avg.Size
S&P Compustat UK	279	0.012	0.038	0.029	2580.7
MSCI UK	.	0.006	0.039	0.004	.

9.3. Switzerland.

Index	Median n	Avg.ROR	Std.Dev.	Skewness	Avg.Size
S&P Compustat CH	46	0.019	0.052	0.049	8566.4
MSCI CH	.	0.011	0.049	0.011	.





10. Appendix II: Correlations between coskewness and skewness in different markets

Factor correlations

US with S&P

RM	SMB	HML	SKS	SMINI
1.000	-0.143	-0.328	0.448	0.953
-0.143	1.000	0.522	-0.148	-0.167
-0.328	0.522	1.000	-0.286	-0.357
0.448	-0.148	-0.286	1.000	0.680
0.953	-0.167	-0.358	0.680	1.000

US with MSCI

1.000	-0.135	-0.283	-0.302	0.932
-0.135	1.000	0.522	0.137	-0.103
-0.283	0.522	1.000	0.356	-0.214
-0.302	0.137	0.356	1.000	-0.020
0.932	-0.103	-0.214	-0.020	1.000

UK with SP

1.000	-0.176	0.336	0.257	0.917
-0.176	1.000	0.075	-0.234	-0.227
0.336	0.075	1.000	0.010	0.283
0.257	-0.234	0.010	1.000	0.588
0.917	-0.227	0.283	0.588	1.000

UK with msci

1.000	-0.195	0.307	0.054	0.707
-0.195	1.000	0.075	-0.061	-0.250
0.307	0.075	1.000	-0.086	0.223
0.054	-0.061	-0.086	1.000	0.546
0.707	-0.250	0.223	0.546	1.000

Ch with sp

1.000	-0.522	-0.306	-0.081	0.668
-0.522	1.000	0.591	0.433	-0.077
-0.306	0.591	1.000	0.685	0.271
-0.081	0.433	0.685	1.000	0.676
0.668	-0.077	0.271	0.676	1.000

CH with msci

1.000	-0.325	0.073	0.004	0.6803
-0.325	1.000	0.591	0.607	-0.080
0.073	0.591	1.000	0.694	0.172
0.004	0.607	0.694	1.000	0.364
0.680	-0.080	0.172	0.364	1.000

11. APPENDIX III: RETURN SORTINGS

11.1. USA.

USA Average Monthly Returns by Size/BM Sortings
B/M Category

Size	low-1	med-2	med-3	high
Low-1	0.029	0.027	0.028	0.023
Med-2	0.030	0.026	0.021	0.028
Med-3	0.032	0.033	0.032	0.007
high	0.021	0.019	0.016	0.028

USA Average Monthly Returns by Size/Pre-Beta Sortings
Pre-Ranking Beta Category

Size	low-1	med-2	med-3	high
Low-1	0.034	0.028	0.016	0.020
Med-2	0.020	0.016	0.029	0.030
Med-3	0.041	0.036	0.035	0.014
high	0.018	0.025	0.027	0.020

USA Average Post-Betas by Size/Pre-Beta Sortings
Pre-Ranking Beta Category

Size	low-1	med-2	med-3	high
low-1	0.219	0.366	-0.140	0.152
med-2	0.012	0.162	0.173	0.213
med-3	-0.723	0.041	0.019	0.193
high	0.253	0.284	0.031	0.118

USA Average Ln(Size) by Size/Pre-Beta Sortings
Pre-Ranking Beta Category

Size	low-1	med-2	med-3	high
low-1	7.954	7.941	8.738	8.677
med-2	9.387	9.357	11.026	11.063
med-3	8.062	7.912	7.895	8.755
high	8.783	8.741	9.429	9.445

USA Average Monthly Returns by Size/Unconditional Skewness Sortings
Pre-Ranking Skewness Category

Size	low-1	med-2	med-3	high
low-1	0.025	0.037	0.024	0.012
med-2	0.020	0.017	0.022	0.028
med-3	0.034	0.025	0.023	0.022
high	0.031	0.024	0.031	0.021

USA Average Monthly Returns by Size/Conditional Skewness Sortings
Pre-Ranking Coskewness Category

Size	low-1	med-2	med-3	high
low-1	0.0323	0.027	0.030	0.022
med-2	0.033	0.023	0.022	0.027
med-3	0.028	0.032	0.032	0.013
high	0.020	0.022	0.024	0.024

11.2. UK.

UK Average Monthly Returns by Size/BM Sortings

	B/M Category			
Size	low-1	med-2	med-3	high
low-1	0.024	0.023	0.027	0.007
med-2	0.037	0.031	0.014	0.013
med-3	0.029	0.034	0.018	-0.006
high	0.015	0.019	0.013	0.012

UK Average Monthly Returns by Size/Pre-Beta Sortings

	Pre-Ranking Beta Category			
Size	low-1	med-2	med-3	high
low-1	0.029	0.035	0.014	0.002
med-2	0.024	0.017	0.020	0.017
med-3	0.033	0.036	0.029	-0.004
high	0.022	0.019	0.009	0.011

UK Average Post-Betas by Size/Pre-Beta Sortings

	Pre-Ranking Beta Category			
Size	low-1	med-2	med-3	high
low-1	0.252	0.182	-0.062	0.641
med-2	0.138	0.166	0.266	0.121
med-3	-0.511	-0.265	-0.264	0.523
high	0.100	0.155	-0.198	0.316

UK Average Ln(Size) by Size/Pre-Beta Sortings

	Pre-Ranking Beta Category			
Size	low-1	med-2	med-3	high
low-1	4.63	4.22	5.47	5.34
med-2	6.54	6.43	9.39	8.95
med-3	4.80	4.75	4.80	5.54
high	5.61	5.67	6.51	6.73

UK Average Monthly Returns by Size/Unconditional Skewness Sortings

	Pre-Ranking Skewness Category			
Size	low-1	med-2	med-3	high
low-1	0.027	0.032	0.018	-0.004
med-2	0.019	0.014	0.003	0.010
med-3	0.035	0.031	0.028	0.003
high	0.029	0.028	0.018	0.012

UK Average Monthly Returns by Size/Conditional Skewness Sortings

	Pre-Ranking Coskewness Category			
Size	low-1	med-2	med-3	high
low-1	0.027	0.029	0.016	0.001
med-2	0.034	0.015	0.019	0.014
med-3	0.025	0.041	0.025	-0.003
high	0.024	0.024	0.014	0.014

11.3. Switzerland.

CH Average Monthly Returns by Size/BM Sortings

	B/M Category			
Size	low-1	med-2	med-3	high
low-1	0.013	0.021	0.019	0.008
med-2	0.009	0.010	0.025	0.015
med-3	0.022	0.023	0.018	0.002
high	0.005	0.013	0.009	0.013

CH Average Monthly Returns by Size/Pre-Beta Sortings

	Pre-Ranking Beta Category			
Size	low-1	med-2	med-3	high
low-1	0.015	0.019	0.018	0.001
med-2	0.005	0.008	0.010	0.014
med-3	0.024	0.023	0.048	0.002
high	0.007	0.012	0.006	0.014

CH Average Post-Betas by Size/Pre-Beta Sortings

	Pre-Ranking Beta Category			
Size	low-1	med-2	med-3	high
low-1	0.133	0.239	0.049	0.578
med-2	0.092	0.090	0.048	0.008
med-3	-0.410	-0.029	1.893	0.556
high	0.279	0.244	0.132	0.276

CH Average Ln(Size) by Size/Pre-Beta Sortings

	Pre-Ranking Beta Category			
Size	low-1	med-2	med-3	high
low-1	4.241	4.223	5.670	5.474
med-2	6.798	6.526	9.818	9.416
med-3	4.428	4.336	4.455	6.039
high	5.762	5.877	6.979	6.957

CH Average Monthly Returns by Size/Unconditional Skewness Sortings

Pre-Ranking Skewness Category

Size low-1 med-2 med-3 high

low-1	0.012	0.021	0.018	0.005
med-2	0.006	0.011	0.010	0.016
med-3	0.018	0.018	0.016	0.006
high	0.011	0.014	0.024	0.007

CH Average Monthly Returns by Size/Conditional Skewness Sortings

	Pre-Ranking Coskewness Category			
Size	low-1	med-2	med-3	high
low-1	0.013	0.021	0.013	-0.005
med-2	0.007	0.006	0.013	0.024
med-3	0.020	0.020	0.032	0.003
high	0.011	0.020	0.012	0.014

12. Appendix IV: Factor Information

(Using S&P Compustat)

		RM	SMB	HML	SKS	SMINI
US	mean	0.013	-0.003	-0.025	0.002	0.014
	std	0.041	0.026	0.036	0.030	0.050
UK	mean	0.004	-0.000	-0.020	-0.006	0.003
	std	0.038	0.038	0.039	0.035	0.051
CH	mean	0.014	-0.012	-0.011	-0.000	0.013
	std	0.052	0.044	0.055	0.079	0.076

(Using MSCI)

		RM	SMB	HML	SKS	SMINI
US	mean	0.005	-0.003	-0.025	-0.002	0.012
	std	0.042	0.026	0.036	0.022	0.039
UK	mean	-0.002	-0.000	-0.020	-0.008	-0.000
	std	0.039	0.038	0.039	0.039	0.044
CH	mean	0.006	-0.012	-0.011	-0.002	0.012
	std	0.049	0.043	0.055	0.057	0.048

13. Appendix V: Factor correlations

US with S&P

	RM	SMB	HML	SKS	SMINI
RM	1.000	-0.143	-0.328	0.448	0.953
SMB	-0.143	1.000	0.522	-0.148	-0.167
HML	-0.328	0.522	1.000	-0.286	-0.358
SKS	0.448	-0.148	-0.286	1.000	0.680
SMINI	0.953	-0.167	-0.358	0.680	1.000

US with MSCI

	RM	SMB	HML	SKS	SMINI
RM	1.000	-0.135	-0.283	-0.302	0.932
SMB	-0.135	1.000	0.522	0.137	-0.103
HML	-0.283	0.522	1.000	0.356	-0.214
SKS	-0.302	0.137	0.356	1.000	-0.020
SMINI	0.932	-0.103	-0.214	-0.020	1.000

UK with SP

	RM	SMB	HML	SKS	SMINI
RM	1.000	-0.176	0.336	0.257	0.917
SMB	-0.176	1.000	0.075	-0.234	-0.227
HML	0.336	0.075	1.000	0.010	0.283
SKS	0.257	-0.234	0.010	1.000	0.588
SMINI	0.917	-0.227	0.283	0.588	1.000

UK with msci

	RM	SMB	HML	SKS	SMINI
RM	1.000	-0.195	0.307	0.054	0.707
SMB	-0.195	1.000	0.075	-0.061	-0.250
HML	0.307	0.075	1.000	-0.086	0.223
SKS	0.054	-0.061	-0.086	1.000	0.546
SMINI	0.707	-0.250	0.223	0.546	1.000

Ch with sp

	RM	SMB	HML	SKS	SMINI
RM	1.000	-0.522	-0.306	-0.081	0.668
SMB	-0.522	1.000	0.591	0.433	-0.077
HML	-0.306	0.591	1.000	0.685	0.271
SKS	-0.081	0.433	0.685	1.000	0.676
SMINI	0.668	-0.077	0.271	0.676	1.000

CH with msci

	RM	SMB	HML	SKS	SMINI
RM	1.000	-0.325	0.073	0.004	0.680
SMB	-0.325	1.000	0.591	0.607	-0.080
HML	0.073	0.591	1.000	0.694	0.172
SKS	0.004	0.607	0.694	1.000	0.364
SMINI	0.680	-0.080	0.172	0.364	1.000

14. Appendix VI: RMSE of Selected Models

14.1. USA.

	M1	M2	M3	M4	M5	M6	M7
S1	0.029	0.025	0.019	0.012	0.008	0.019	0.015
S2	0.020	0.022	0.024	0.029	0.025	0.019	0.012
S3	0.008	0.016	0.014	0.020	0.022	0.022	0.028
S4	0.025	0.019	0.012	0.008	0.016	0.014	0.020
S5	0.022	0.022	0.023	0.016	0.016	0.010	0.006
B1	0.016	0.015	0.014	0.015	0.024	0.023	0.016
B2	0.016	0.011	0.006	0.016	0.015	0.014	0.015
B3	0.024	0.022	0.015	0.016	0.011	0.006	0.011
B4	0.014	0.014	0.014	0.020	0.022	0.015	0.016
B5	0.011	0.006	0.011	0.014	0.014	0.014	0.020

14.2. UK.

	M1	M2	M3	M4	M5	M6	M7
S1	0.055	0.043	0.034	0.025	0.009	0.020	0.018
S2	0.025	0.028	0.036	0.055	0.043	0.033	0.025
S3	0.009	0.019	0.017	0.022	0.027	0.027	0.055
S4	0.043	0.032	0.025	0.009	0.018	0.017	0.024
S5	0.027	0.025	0.039	0.027	0.023	0.019	0.007
B1	0.018	0.018	0.023	0.028	0.035	0.039	0.027
B2	0.023	0.019	0.007	0.018	0.018	0.023	0.028
B3	0.035	0.039	0.027	0.022	0.019	0.007	0.016
B4	0.017	0.021	0.027	0.027	0.038	0.026	0.022
B5	0.019	0.006	0.014	0.017	0.019	0.027	0.025

14.3. CH.

	M1	M2	M3	M4	M5	M6	M7
S1	0.061	0.052	0.042	0.171	0.023	0.029	0.077
S2	0.042	0.044	0.046	0.056	0.045	0.036	0.151
S3	0.021	0.028	0.071	0.033	0.043	0.040	0.057
S4	0.046	0.037	0.152	0.021	0.028	0.072	0.034
S5	0.044	0.041	0.051	0.035	0.027	0.121	0.017
B1	0.025	0.058	0.032	0.040	0.029	0.051	0.035
B2	0.027	0.121	0.017	0.025	0.058	0.032	0.040
B3	0.029	0.051	0.034	0.026	0.121	0.017	0.024
B4	0.058	0.029	0.040	0.029	0.050	0.034	0.026
B5	0.121	0.017	0.023	0.058	0.029	0.034	0.029

15. Appendix VII: Adjusted R-Squared of Selected Models

15.1. USA.

	M1	M2	M3	M4	M5	M6	M7
S1	0.639	0.681	0.764	0.912	0.963	0.821	0.878
S2	0.767	0.763	0.740	0.649	0.682	0.767	0.911
S3	0.964	0.872	0.895	0.774	0.764	0.793	0.657
S4	0.684	0.764	0.912	0.964	0.867	0.892	0.770
S5	0.766	0.794	0.764	0.867	0.827	0.928	0.978
B1	0.864	0.877	0.882	0.883	0.750	0.764	0.867
B2	0.827	0.928	0.978	0.864	0.877	0.882	0.882
B3	0.750	0.785	0.880	0.827	0.928	0.981	0.935
B4	0.895	0.883	0.895	0.815	0.796	0.883	0.832
B5	0.929	0.981	0.935	0.894	0.886	0.898	0.816

15.2. UK.

	M1	M2	M3	M4	M5	M6	M7
S1	0.168	0.375	0.524	0.730	0.943	0.749	0.795
S2	0.723	0.634	0.568	0.165	0.383	0.564	0.729
S3	0.943	0.770	0.813	0.784	0.658	0.756	0.160
S4	0.373	0.572	0.729	0.944	0.797	0.816	0.750
S5	0.660	0.791	0.578	0.757	0.786	0.838	0.971
B1	0.791	0.796	0.751	0.632	0.569	0.578	0.757
B2	0.786	0.838	0.971	0.791	0.796	0.751	0.632
B3	0.569	0.575	0.755	0.796	0.844	0.970	0.825
B4	0.811	0.804	0.656	0.753	0.595	0.762	0.807
B5	0.843	0.972	0.866	0.813	0.824	0.655	0.786

15.3. CH.

	M1	M2	M3	M4	M5	M6	M7
S1	0.289	0.258	0.427	0.392	0.732	0.662	0.598
S2	0.406	0.265	0.434	0.388	0.453	0.585	0.523
S3	0.792	0.681	0.654	0.643	0.296	0.560	0.385
S4	0.432	0.573	0.512	0.786	0.687	0.652	0.625
S5	0.271	0.546	0.497	0.658	0.772	0.691	0.861
B1	0.743	0.767	0.661	0.386	0.774	0.497	0.658
B2	0.772	0.691	0.861	0.743	0.767	0.661	0.386
B3	0.774	0.498	0.679	0.772	0.689	0.860	0.748
B4	0.769	0.705	0.388	0.772	0.496	0.676	0.770
B5	0.685	0.859	0.770	0.769	0.703	0.552	0.769

16. Appendix VIII: Akaike Information Criterion (AIC) of Selected Models (*100)

16.1. USA.

	M1	M2	M3	M4	M5	M6	M7
S1	0.089	0.067	0.037	0.015	0.007	0.038	0.025
S2	0.042	0.049	0.062	0.088	0.067	0.036	0.015
S3	0.007	0.027	0.021	0.041	0.050	0.050	0.086
S4	0.067	0.037	0.015	0.007	0.028	0.022	0.042
S5	0.049	0.050	0.059	0.028	0.027	0.013	0.004
B1	0.029	0.025	0.022	0.025	0.061	0.059	0.028
B2	0.027	0.013	0.004	0.029	0.025	0.022	0.025
B3	0.061	0.055	0.026	0.028	0.013	0.004	0.014
B4	0.022	0.022	0.023	0.045	0.052	0.026	0.027
B5	0.013	0.004	0.014	0.022	0.021	0.022	0.046

16.2. UK.

	M1	M2	M3	M4	M5	M6	M7
S1	0.312	0.193	0.123	0.065	0.009	0.041	0.034
S2	0.064	0.082	0.133	0.316	0.193	0.114	0.066
S3	0.009	0.038	0.031	0.051	0.077	0.076	0.318
S4	0.196	0.111	0.066	0.009	0.034	0.031	0.059
S5	0.077	0.065	0.161	0.077	0.056	0.040	0.005
B1	0.035	0.034	0.059	0.084	0.136	0.161	0.077
B2	0.056	0.040	0.005	0.035	0.034	0.059	0.084
B3	0.136	0.164	0.078	0.054	0.039	0.005	0.029
B4	0.032	0.047	0.079	0.079	0.157	0.076	0.052
B5	0.040	0.005	0.023	0.032	0.042	0.080	0.069

16.3. CH.

	M1	M2	M3	M4	M5	M6	M7
S1	0.388	0.286	0.187	3.026	0.057	0.086	0.621
S2	0.187	0.202	0.220	0.337	0.212	0.137	2.397
S3	0.045	0.081	0.538	0.113	0.195	0.173	0.338
S4	0.221	0.141	2.451	0.046	0.080	0.542	0.119
S5	0.202	0.178	0.279	0.134	0.076	1.569	0.030
B1	0.066	0.366	0.109	0.172	0.090	0.279	0.134
B2	0.076	1.569	0.030	0.066	0.366	0.109	0.172
B3	0.090	0.281	0.127	0.077	1.594	0.031	0.066
B4	0.366	0.095	0.173	0.091	0.285	0.129	0.078
B5	1.624	0.031	0.060	0.370	0.097	0.128	0.093

17. Appendix IX: Schwarz Information Criterion of Selected Models (*100)

17.1. USA.

	M1	M2	M3	M4	M5	M6	M7
S1	0.094	0.070	0.038	0.016	0.007	0.039	0.026
S2	0.044	0.052	0.065	0.094	0.072	0.039	0.016
S3	0.007	0.029	0.023	0.045	0.053	0.054	0.092
S4	0.072	0.040	0.016	0.007	0.030	0.024	0.045
S5	0.053	0.054	0.066	0.031	0.030	0.014	0.005
B1	0.032	0.028	0.024	0.027	0.067	0.066	0.031
B2	0.030	0.014	0.005	0.032	0.028	0.024	0.027
B3	0.067	0.062	0.029	0.031	0.014	0.004	0.016
B4	0.025	0.025	0.026	0.051	0.061	0.030	0.031
B5	0.015	0.004	0.017	0.026	0.025	0.026	0.053

17.2. UK.

	M1	M2	M3	M4	M5	M6	M7
S1	0.328	0.203	0.129	0.069	0.010	0.043	0.036
S2	0.068	0.086	0.140	0.340	0.208	0.122	0.072
S3	0.010	0.041	0.034	0.055	0.083	0.082	0.342
S4	0.211	0.120	0.071	0.010	0.036	0.033	0.063
S5	0.083	0.070	0.178	0.085	0.062	0.044	0.005
B1	0.038	0.038	0.065	0.093	0.150	0.178	0.085
B2	0.062	0.044	0.005	0.038	0.038	0.065	0.093
B3	0.150	0.185	0.088	0.061	0.044	0.006	0.033
B4	0.036	0.053	0.090	0.089	0.183	0.089	0.060
B5	0.046	0.005	0.026	0.037	0.049	0.093	0.080

17.3. CH.

	M1	M2	M3	M4	M5	M6	M7
S1	0.407	0.300	0.197	3.181	0.060	0.090	0.653
S2	0.196	0.213	0.231	0.363	0.229	0.147	2.583
S3	0.048	0.088	0.580	0.122	0.210	0.186	0.364
S4	0.238	0.152	2.640	0.050	0.086	0.584	0.128
S5	0.218	0.192	0.309	0.148	0.084	1.732	0.033
B1	0.073	0.404	0.120	0.190	0.099	0.309	0.148
B2	0.084	1.732	0.033	0.073	0.404	0.120	0.190
B3	0.099	0.319	0.144	0.087	1.805	0.035	0.074
B4	0.414	0.108	0.196	0.103	0.330	0.150	0.090
B5	1.885	0.036	0.070	0.429	0.112	0.148	0.108

18. Appendix X: Wald Chi-Square Test of Selected Models

18.1. USA.

SIZE SORTING ACROSS FIVE PORTFOLIOS ON THE SEVEN MODELS
—– LSUR: Results for Linear Hypothesis Testing —–

MODEL 1:	Wald Chi-SQ stat	6.295	Prob.	0.012
MODEL 2:	Wald Chi-SQ stat	20.053	Prob.	0.000
MODEL 3:	Wald Chi-SQ stat	6.596	Prob.	0.010
MODEL 4:	Wald Chi-SQ stat	21.976	Prob.	0.000
MODEL 5:	Wald Chi-SQ stat	6.918	Prob.	0.009
MODEL 6:	Wald Chi-SQ stat	22.910	Prob.	0.000
MODEL 7:	Wald Chi-SQ stat	20.474	Prob.	0.000

B/M SORTING ACROSS FIVE PORTFOLIOS ON THE SEVEN MODELS
—– LSUR: Results for Linear Hypothesis Testing —–

MODEL 1:	Wald Chi-SQ stat	114.281	Prob.	0.000
MODEL 2:	Wald Chi-SQ stat	20.474	Prob.	0.000
MODEL 3:	Wald Chi-SQ stat	20.474	Prob.	0.000
MODEL 4:	Wald Chi-SQ stat	24.990	Prob.	0.000
MODEL 5:	Wald Chi-SQ stat	162.994	Prob.	0.000
MODEL 6:	Wald Chi-SQ stat	27.228	Prob.	0.000
MODEL 7:	Wald Chi-SQ stat	186.303	Prob.	0.000

18.2. UK.

SIZE SORTING ACROSS FIVE PORTFOLIOS ON THE SEVEN MODELS
— – LSUR: Results for Linear Hypothesis Testing ——————

Model1:	WaldChi-SQ(1)statistic	11.640	Prob.	0.001
Model2:	WaldChi-SQ(1)statistic	346.520	Prob.	0.000
Model3:	WaldChi-SQ(1)statistic	9.484	Prob.	0.002
Model4:	WaldChi-SQ(1)statistic	414.915	Prob.	0.000
Model5:	WaldChi-SQ(1)statistic	10.999	Prob.	0.001
Model6:	WaldChi-SQ(1)statistic	474.024	Prob.	0.000
Model7:	WaldChi-SQ(1)statistic	9.401	Prob.	0.002

B/M SORTING ACROSS FIVE PORTFOLIOS ON THE SEVEN MODELS
—– LSUR: Results for Linear Hypothesis Testing ——————

Model1:	Wald Chi-Q(1)statistic	232.468	Prob.	0.000
Model2:	WaldChi-SQ(1)statistic	9.401	Prob.	0.002
Model3:	WaldChi-SQ(1)statistic	9.401	Prob.	0.002
Model4:	WaldChi-SQ(1)statistic	8.968	Prob.	0.003
Model5:	WaldChi-SQ(1)statistic	277.844	Prob.	0.000
Model6:	WaldChi-SQ(1)statistic	6.828	Prob.	0.009
Model7:	WaldChi-SQ(1)statistic	293.193	Prob.	0.000

18.3. CH.

SIZE SORTING SCROSS FIVE PORTFOLIOS ON THE SEVEN MODELS

—– LSUR: Results for Linear Hypothesis Testing ————————

Model1:	WaldChiSqstat	0.006	Prob.	0.940
Model2:	WaldChiSqstat	3.767	Prob.	0.052
Model3:	WaldChiSqstat	0.006	Prob.	0.937
Model4:	WaldChiSqstat	4.365	Prob.	0.037
Model5:	WaldChiSqstat	0.005	Prob.	0.942
Model6:	WaldChiSqstat	4.598	Prob.	0.032
Model7:	WaldChiSqstat	0.005	Prob.	0.942

B/M SORTING SCROSS FIVE PORTFOLIOS ON THE SEVEN MODELS

—– LSUR: Results for Linear Hypothesis Testing ————————

Model1:	WaldChiSqstat	11.734	Prob.	0.001
Model2:	WaldChiSqstat	0.005	Prob.	0.942
Model3:	WaldChiSqstat	0.005	Prob.	0.942
Model4:	WaldChiSqstat	0.032	Prob.	0.858
Model5:	WaldChiSqstat	9.897	Prob.	0.002
Model6:	WaldChiSqstat	0.017	Prob.	0.896
Model7:	WaldChiSqstat	7.136	Prob.	0.008

19. APPENDIX XI: COEFFICIENTS OF SELECTED MODELS IN OLS

19.1. USA.

USA Coefficients and T-Stats for Model 1: r=a+b*RM+e

	a	b	t(a)	t(b)
S1	0.00681	0.89	2.42	12.8
S2	0.0115	0.871	4.84	14.8
S3	0.0102	0.764	5.32	16.2
S4	0.0116	0.908	9.25	29.3
S5	0.0127	0.998	13.8	43.6
B1	0.0137	0.968	7.11	20.3
B2	0.0147	0.999	9.87	27
B3	0.0103	0.803	4.53	14.2
B4	0.00883	0.936	4.35	18.6
B5	0.0047	1	2.16	18.6

USA Coefficients and T-Stats for Model 2: r=a+b*RM+c*SKS+e

	a	b	c	t(a)	t(b)	t(c)
S1	0.00686	0.889	-0.0263	2.41	12.6	-0.18
S2	0.0113	0.875	0.0973	4.71	14.7	0.793
S3	0.00981	0.771	0.156	5.14	16.3	1.6
S4	0.0113	0.914	0.136	9.09	29.8	2.14
S5	0.0127	1	0.0355	13.6	43.4	0.745
B1	0.0142	0.957	-0.234	7.48	20.4	-2.4
B2	0.0137	1.02	0.478	11.1	33.4	7.56
B3	0.0103	0.803	-0.00569	4.49	14.1	-0.0484
B4	0.0087	0.939	0.0598	4.24	18.5	0.57
B5	0.0047	1	-0.00255	2.14	18.5	-0.0228

USA Coefficients and T-Stats for Model 3: r=a+b*RM+m*SMINI+e

	a	b	m	t(a)	t(b)	t(m)
S1	0.00669	0.879	0.012	1.92	4.2	0.0565
S2	0.0105	0.772	0.106	3.57	4.37	0.591
S3	0.0066	0.42	0.369	2.88	3.04	2.65
S4	0.00821	0.581	0.349	5.64	6.66	3.96
S5	0.00906	0.643	0.38	9.19	10.9	6.36
B1	0.00986	0.595	0.399	4.27	4.29	2.85
B2	0.00816	0.363	0.681	5.34	3.96	7.35
B3	0.00885	0.662	0.151	3.16	3.93	0.887
B4	0.0088	0.933	0.0027	3.5	6.18	0.0177
B5	0.00663	1.19	-0.201	2.49	7.42	-1.24

USA Coefficients and T-Stats for Model 4: r=a+b*RM+s*SMB+h*HML+e

	a	b	s	h	t(a)	t(b)	t(s)	t(h)
S1	0.00573	0.936	0.757	-0.0891	2.09	16.1	7.88	-1.24
S2	0.013	0.935	0.648	0.0301	5.99	20.4	8.53	0.531
S3	0.0116	0.807	0.371	0.0429	5.71	18.8	5.23	0.808
S4	0.0115	0.918	0.153	-0.0119	7.81	29.5	2.97	-0.308
S5	0.0106	0.963	-0.179	-0.0852	12.3	52.8	-5.94	-3.78
B1	0.00731	0.888	-0.16	-0.278	3.78	21.8	-2.36	-5.5
B2	0.0128	0.971	-0.0919	-0.0828	7.26	26.1	-1.49	-1.8
B3	0.0164	0.899	0.438	0.248	8.09	21	6.17	4.68
B4	0.0147	1.02	0.316	0.245	7.68	25.3	4.71	4.89
B5	0.00767	1.03	-0.0224	0.134	2.94	18.7	-0.245	1.96

USA Coefficients and T-Stats for Model 5: r=a+o*RMO+s*SMB+h*HML+e

	a	o	s	h	t(a)	t(o)	t(s)	t(h)
S1	0.00573	0.936	0.724	-0.353	2.09	16.1	7.54	-5.05
S2	0.013	0.935	0.615	-0.234	5.99	20.4	8.1	-4.22
S3	0.0116	0.807	0.342	-0.185	5.71	18.8	4.82	-3.58
S4	0.0115	0.918	0.121	-0.271	7.81	29.5	2.34	-7.22
S5	0.0106	0.963	-0.214	-0.357	12.3	52.8	-7.08	-16.2
B1	0.00731	0.888	-0.191	-0.529	3.78	21.8	-2.83	-10.7
B2	0.0128	0.971	-0.126	-0.357	7.26	26.1	-2.05	-7.96
B3	0.0164	0.899	0.406	-0.00561	8.09	21	5.72	-0.109
B4	0.0147	1.02	0.279	-0.0433	7.68	25.3	4.17	-0.888
B5	0.00767	1.03	-0.059	-0.156	2.94	18.7	-0.645	-2.35

USA Coefficients and T-Stats for Model 6: r=a+o*RMO+s*SMB+h*HML+c*SKS+e

	a	o	s	h	c	t(a)	t(o)	t(s)	t(h)	t(c)
S1	0.00686	0.889	-0.0263	0.0113	0.875	2.41	12.6	-0.18	4.71	14.7
S2	0.0973	0.00981	0.771	0.156	0.0113	0.793	5.14	16.3	1.6	9.09
S3	0.914	0.136	0.0127	1	0.0355	29.8	2.14	13.6	43.4	0.745
S4	0.0142	0.957	-0.234	0.0137	1.02	7.48	20.4	-2.4	11.1	33.4
S5	0.478	0.0103	0.803	-0.00569	0.0087	7.56	4.49	14.1	-0.0484	4.24
B1	0.939	0.0598	0.0047	1	-0.00255	18.5	0.57	2.14	18.5	-0.0228
B2	0.00686	0.889	-0.0263	0.0113	0.875	2.41	12.6	-0.18	4.71	14.7
B3	0.0973	0.00981	0.771	0.156	0.0113	0.793	5.14	16.3	1.6	9.09
B4	0.914	0.136	0.0127	1	0.0355	29.8	2.14	13.6	43.4	0.745
B5	0.0142	0.957	-0.234	0.0137	1.02	7.48	20.4	-2.4	11.1	33.4

USA Coefficients and T-Stats for Model 7: r=a+o*RMO+s*SMB+h*HML+c*SKS+m*SMINI+e

	a	o	s	h	c	m	t(a)	t(o)	t(s)	t(h)	t(c)	t(m)
S1	0.00329	0.612	0.762	-0.0585	-0.105	0.35	0.975	2.21	7.9	-0.776	-0.548	1.21
S2	0.0104	0.618	0.661	0.0678	0.0302	0.351	4.01	2.9	8.91	1.17	0.205	1.58
S3	0.00582	0.0558	0.385	0.117	-0.196	0.815	2.57	0.301	5.95	2.31	-1.53	4.21
S4	0.00702	0.33	0.163	0.0449	-0.173	0.637	4.32	2.47	3.51	1.23	-1.87	4.58
S5	0.00535	0.23	-0.18	-0.0264	-0.422	0.779	8.36	4.38	-9.84	-1.84	-11.6	14.2
B1	-0.00198	-0.466	-0.18	-0.186	-1.08	1.42	-1.25	-3.58	-3.96	-5.25	-11.9	10.5
B2	0.0104	0.74	-0.0639	-0.0386	0.31	0.276	5.87	5.07	-1.26	-0.971	3.07	1.81
B3	0.00921	-0.0706	0.445	0.334	-0.422	1.04	4.17	-0.389	7.05	6.76	-3.36	5.52
B4	0.0122	0.717	0.326	0.279	-0.00545	0.335	5.34	3.81	4.97	5.43	-0.0418	1.71
B5	0.0102	1.39	-0.0209	0.106	0.227	-0.385	3.2	5.29	-0.228	1.48	1.25	-1.41

19.2. UK.

UK Coefficients and T-Stats for Model 1: r=a+b*RM+e

	a	b	t(a)	t(b)
S1	0.0141	0.497	2.66	3.78
S2	0.0122	0.621	2.99	6.12
S3	0.0131	0.735	2.95	6.65
S4	0.0129	0.82	3.73	9.51
S5	0.0151	0.757	5.89	11.9
B1	0.0145	0.649	5.06	9.09
B2	0.0168	0.726	5.54	9.58
B3	0.0156	0.785	4.47	9.03
B4	0.011	0.786	3.12	8.97
B5	0.0131	0.854	3.18	8.32

UK Coefficients and T-Stats for Model 2: r=a+b*RM+c*SKS+e

	a	b	c	t(a)	t(b)	t(c)
S1	0.0145	0.503	-0.64	2.89	4.02	-3.65
S2	0.0127	0.627	-0.674	3.45	6.84	-5.24
S3	0.0136	0.741	-0.695	3.35	7.33	-4.9
S4	0.0133	0.824	-0.514	4.15	10.3	-4.61
S5	0.0149	0.755	0.173	5.9	12	1.95
B1	0.0146	0.65	-0.161	5.14	9.17	-1.62
B2	0.0171	0.729	-0.334	5.84	10	-3.27
B3	0.0155	0.784	0.122	4.44	9.01	0.996
B4	0.0108	0.785	0.163	3.09	8.98	1.33
B5	0.013	0.852	0.17	3.15	8.32	1.18

UK Coefficients and T-Stats for Model 3: r=a+b*RM+m*SMINI+e

	a	b	m	t(a)	t(b)	t(m)
S1	0.00962	0.0451	0.568	1.84	0.244	3.34
S2	0.0078	0.174	0.561	1.99	1.26	4.42
S3	0.00736	0.153	0.731	1.79	1.06	5.49
S4	0.00706	0.225	0.747	2.44	2.2	7.96
S5	0.00838	0.0756	0.855	7.91	2.02	24.9
B1	0.01	0.19	0.576	4.03	2.17	7.15
B2	0.0115	0.184	0.68	4.62	2.09	8.41
B3	0.00835	0.0434	0.932	3.38	0.497	11.6
B4	0.00417	0.0938	0.87	1.55	0.99	9.99
B5	0.00476	0.00362	1.07	1.59	0.0341	11

UK Coefficients and T-Stats for Model 4: r=a+b*RM+s*SMB+h*HML+e

	a	b	s	h	t(a)	t(b)	t(s)	t(h)
S1	0.0116	0.665	0.934	-0.246	2.46	5.88	8.38	-1.99
S2	0.0142	0.684	0.754	0.0274	4.11	8.27	9.25	0.303
S3	0.0169	0.755	0.667	0.139	4.07	7.6	6.82	1.29
S4	0.0138	0.848	0.333	0.0108	3.74	9.62	3.84	0.112
S5	0.0174	0.683	-0.239	0.158	6.4	10.5	-3.73	2.23
B1	0.0129	0.661	-0.122	-0.0742	4.06	8.65	-1.62	-0.892
B2	0.0198	0.676	0.0304	0.164	5.85	8.34	0.381	1.86
B3	0.0219	0.668	-0.0357	0.359	5.85	7.44	-0.404	3.67
B4	0.0134	0.736	-0.056	0.142	3.38	7.77	-0.601	1.38
B5	0.0139	0.82	-0.153	0.0623	3.01	7.39	-1.4	0.515

UK Coefficients and T-Stats for Model 5: r=a+o*RMO+s*SMB+h*HML+e

	a	o	s	h	t(a)	t(o)	t(s)	t(h)
S1	0.0116	0.665	0.824	0.0203	2.46	5.88	7.5	0.177
S2	0.0142	0.684	0.641	0.301	4.11	8.27	7.98	3.59
S3	0.0169	0.755	0.543	0.441	4.07	7.6	5.63	4.38
S4	0.0138	0.848	0.194	0.35	3.74	9.62	2.26	3.91
S5	0.0174	0.683	-0.352	0.432	6.4	10.5	-5.56	6.53
B1	0.0129	0.661	-0.231	0.19	4.06	8.65	-3.11	2.45
B2	0.0198	0.676	-0.081	0.435	5.85	8.34	-1.03	5.28
B3	0.0219	0.668	-0.146	0.626	5.85	7.44	-1.67	6.88
B4	0.0134	0.736	-0.177	0.437	3.38	7.77	-1.93	4.55
B5	0.0139	0.82	-0.288	0.39	3.01	7.39	-2.67	3.47

UK Coefficients and T-Stats for Model 6: r=a+o*RMO+s*SMB+h*HML+c*SKS+e

	a	o	s	h	c	t(a)	t(o)	t(s)	t(h)	t(c)
S1	0.0145	0.503	-0.64	0.0127	0.627	2.89	4.02	-3.65	3.45	6.84
S2	-0.674	0.0136	0.741	-0.695	0.0133	-5.24	3.35	7.33	-4.9	4.15
S3	0.824	-0.514	0.0149	0.755	0.173	10.3	-4.61	5.9	12	1.95
S4	0.0146	0.65	-0.161	0.0171	0.729	5.14	9.17	-1.62	5.84	10
S5	-0.334	0.0155	0.784	0.122	0.0108	-3.27	4.44	9.01	0.996	3.09
B1	0.785	0.163	0.013	0.852	0.17	8.98	1.33	3.15	8.32	1.18
B2	0.0145	0.503	-0.64	0.0127	0.627	2.89	4.02	-3.65	3.45	6.84
B3	-0.674	0.0136	0.741	-0.695	0.0133	-5.24	3.35	7.33	-4.9	4.15
B4	0.824	-0.514	0.0149	0.755	0.173	10.3	-4.61	5.9	12	1.95
B5	0.0146	0.65	-0.161	0.0171	0.729	5.14	9.17	-1.62	5.84	10

UK Coefficients and T-Stats for Model 7: r=a+o*RMO+s*SMB+h*HML+c*SKS+m*SMINI+e

	a	o	s	h	c	m	t(a)	t(o)	t(s)	t(h)	t(c)	t(m)
S1	0.00133	-0.082	1.02	-0.401	-0.284	1.01	0.333	-0.644	9.81	-3.82	-2	8.36
S2	0.00593	-0.0344	0.721	-0.0465	-0.552	0.934	2.71	-0.492	12.7	-0.805	-7.08	14
S3	0.00747	-0.105	0.595	0.0723	-0.738	1.11	2.87	-1.26	8.78	1.05	-7.95	14
S4	0.00478	0.0216	0.259	-0.0504	-0.722	1.06	2.56	0.361	5.31	-1.02	-10.8	18.7
S5	0.00835	0.0264	-0.165	0.0218	-0.252	0.891	8.5	0.842	-6.46	0.843	-7.19	29.9
B1	0.00687	0.096	-0.177	-0.113	-0.503	0.724	2.8	1.22	-2.76	-1.75	-5.74	9.69
B2	0.0131	-0.00942	-0.0835	0.148	-0.726	0.862	6.27	-0.141	-1.53	2.69	-9.74	13.6
B3	0.0118	-0.0472	0.062	0.199	-0.233	0.976	4.44	-0.555	0.893	2.84	-2.45	12.1
B4	0.00325	0.0614	0.0797	-0.0369	-0.114	0.936	1.05	0.622	0.991	-0.453	-1.03	9.97
B5	0.00158	-0.0339	-0.0144	-0.142	-0.226	1.17	0.465	-0.312	-0.163	-1.59	-1.86	11.4

19.3. CH.

CH Coefficients and T-Stats for Model 1: r=a+b*RM+e

	a	b	t(a)	t(b)
S1	0.00296	0.641	0.507	5.36
S2	0.00676	0.559	1.15	4.64
S3	0.0058	0.515	1.42	6.15
S4	0.0134	0.609	3.04	6.78
S5	0.0123	0.693	4.44	12.2
B1	0.0114	0.678	3.42	9.95
B2	0.0126	0.771	3.1	9.3
B3	0.0127	0.582	2.54	5.7
B4	0.00822	0.546	1.97	6.4
B5	0.00461	0.687	0.812	5.91

CH Coefficients and T-Stats for Model 2: r=a+b*RM+c*SKS+e

	a	b	c	t(a)	t(b)	t(c)
S1	0.00367	0.7	-0.168	0.625	5.38	-1.14
S2	0.0069	0.57	-0.0318	1.16	4.33	-0.214
S3	0.00608	0.539	-0.0678	1.47	5.89	-0.656
S4	0.0132	0.597	0.0338	2.98	6.08	0.305
S5	0.0126	0.716	-0.066	4.51	11.6	-0.943
B1	0.0122	0.742	-0.182	3.69	10.2	-2.2
B2	0.0114	0.676	0.272	2.88	7.69	2.74
B3	0.0126	0.575	0.0208	2.5	5.15	0.165
B4	0.00874	0.589	-0.123	2.09	6.35	-1.17
B5	0.00492	0.713	-0.0743	0.859	5.62	-0.518

CH Coefficients and T-Stats for Model 3: r=a+b*RM+m*SMINI+e

	a	b	m	t(a)	t(b)	t(m)
S1	-0.00287	0.176	0.572	-0.498	1.04	3.7
S2	-0.00185	-0.127	0.845	-0.343	-0.8	5.83
S3	0.000255	0.0742	0.543	0.0664	0.658	5.28
S4	0.00604	0.0266	0.717	1.56	0.235	6.94
S5	0.00546	0.146	0.673	3.14	2.87	14.5
B1	0.00419	0.105	0.706	1.69	1.44	10.6
B2	0.00372	0.0677	0.866	1.24	0.771	10.8
B3	0.00469	-0.0524	0.781	1.05	-0.401	6.55
B4	0.00664	0.42	0.155	1.54	3.32	1.34
B5	-0.00332	0.0558	0.777	-0.628	0.36	5.49

CH Coefficients and T-Stats for Model 4: r=a+b*RM+s*SMB+h*HML+e

	a	b	s	h	t(a)	t(b)	t(s)	t(h)
S1	0.0117	0.802	0.807	0.295	2.15	6.9	4.96	2.05
S2	0.0167	0.717	0.848	0.399	3.15	6.33	5.34	2.84
S3	0.0116	0.605	0.487	0.238	2.98	7.27	4.18	2.31
S4	0.0199	0.655	0.394	0.404	4.78	7.37	3.16	3.67
S5	0.0113	0.669	-0.109	-0.0221	3.88	10.8	-1.25	-0.286
B1	0.00944	0.661	-0.128	-0.113	2.73	8.94	-1.23	-1.23
B2	0.0141	0.722	-0.0725	0.243	3.37	8.06	-0.578	2.19
B3	0.0198	0.65	0.482	0.397	4.16	6.39	3.38	3.14
B4	0.0113	0.55	0.136	0.235	2.64	6.01	1.06	2.07
B5	0.0145	0.832	0.808	0.426	2.85	7.66	5.32	3.16

CH Coefficients and T-Stats for Model 5: r=a+o*RMO+s*SMB+h*HML+e

	a	o	s	h	t(a)	t(o)	t(s)	t(h)
S1	0.0117	0.802	0.389	0.511	2.15	6.9	2.58	3.63
S2	0.0167	0.717	0.475	0.592	3.15	6.33	3.22	4.32
S3	0.0116	0.605	0.172	0.401	2.98	7.27	1.59	3.98
S4	0.0199	0.655	0.0526	0.581	4.78	7.37	0.456	5.4
S5	0.0113	0.669	-0.457	0.158	3.88	10.8	-5.66	2.1
B1	0.00944	0.661	-0.472	0.0653	2.73	8.94	-4.91	0.729
B2	0.0141	0.722	-0.449	0.438	3.37	8.06	-3.86	4.04
B3	0.0198	0.65	0.143	0.572	4.16	6.39	1.08	4.64
B4	0.0113	0.55	-0.15	0.383	2.64	6.01	-1.26	3.46
B5	0.0145	0.832	0.375	0.65	2.85	7.66	2.66	4.94

CH Coefficients and T-Stats for Model 6: r=a+o*RMO+s*SMB+h*HML+c*SKS+e

	a	o	s	h	c	t(a)	t(o)	t(s)	t(h)	t(c)
S1	0.00367	0.7	-0.168	0.0069	0.57	0.625	5.38	-1.14	1.16	4.33
S2	-0.0318	0.00608	0.539	-0.0678	0.0132	-0.214	1.47	5.89	-0.656	2.98
S3	0.597	0.0338	0.0126	0.716	-0.066	6.08	0.305	4.51	11.6	-0.943
S4	0.0122	0.742	-0.182	0.0114	0.676	3.69	10.2	-2.2	2.88	7.69
S5	0.272	0.0126	0.575	0.0208	0.00874	2.74	2.5	5.15	0.165	2.09
B1	0.589	-0.123	0.00492	0.713	-0.0743	6.35	-1.17	0.859	5.62	-0.518
B2	0.00367	0.7	-0.168	0.0069	0.57	0.625	5.38	-1.14	1.16	4.33
B3	-0.0318	0.00608	0.539	-0.0678	0.0132	-0.214	1.47	5.89	-0.656	2.98
B4	0.597	0.0338	0.0126	0.716	-0.066	6.08	0.305	4.51	11.6	-0.943
B5	0.0122	0.742	-0.182	0.0114	0.676	3.69	10.2	-2.2	2.88	7.69

CH Coefficients and T-Stats for Model 7: r=a+o*RMO+s*SMB+h*HML+c*SKS+m*SMINI+e

	a	o	s	h	c	m	t(a)	t(o)	t(s)	t(h)	t(c)	t(m)
S1	0.00592	0.308	0.808	0.344	-0.543	0.835	1.2	2.18	5.65	2.63	-4.13	5.92
S2	0.00806	0.0186	0.876	0.406	-0.522	1.09	1.9	0.153	7.12	3.6	-4.61	9.01
S3	0.00609	0.152	0.499	0.258	-0.396	0.73	1.85	1.61	5.24	2.95	-4.53	7.77
S4	0.0128	0.0854	0.419	0.401	-0.394	0.879	3.9	0.91	4.43	4.63	-4.53	9.42
S5	0.00435	0.109	-0.0861	-0.0173	-0.417	0.875	4.34	3.79	-2.97	-0.652	-15.6	30.6
B1	0.00215	0.0561	-0.116	-0.0784	-0.563	0.986	1.43	1.3	-2.65	-1.96	-14.1	23
B2	0.00512	0.0571	-0.00691	0.154	-0.13	0.909	1.65	0.639	-0.0767	1.87	-1.57	10.2
B3	0.0119	0.023	0.51	0.394	-0.436	0.969	3.1	0.208	4.58	3.86	-4.26	8.83
B4	0.0102	0.425	0.12	0.288	-0.294	0.267	2.34	3.41	0.95	2.5	-2.54	2.15
B5	0.00666	0.189	0.826	0.451	-0.554	1.03	1.63	1.61	6.98	4.16	-5.1	8.86

20 Appendix XII: Coefficients of B/M Conditional Three Factor in LSUR

20.1 USA

USA Coefficients and T-Stats for Model 8 (Size sort): r=a+b*ln(BM)+c*RMO+d*RMO*ln(BM)+e*SMB+f*SMB*ln(BM)+g*HML+h*HML*ln(BM)+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
S1	-0.00262	-0.0138	0.794	-0.245	1.33	0.803	-1.24	-1.31	-0.243	-0.958	4.32	-0.962	4.05	1.76	-4.95	-3.67
S2	0.00875	-0.00468	1.03	0.101	-0.595	-1.47	-0.0787	0.202	0.764	-0.34	3.55	0.3	-1.42	-2.89	-0.208	0.433
S3	-0.0156	-0.0306	0.0746	-0.813	0.296	-0.0477	-1.3	-1.28	-1.01	-1.8	0.255	-2.6	0.528	-0.076	-3.03	-2.63
S4	-0.00231	-0.0124	0.62	-0.26	-0.261	-0.344	-0.317	-0.041	-0.223	-1.32	2.45	-1.19	-0.694	-1.01	-0.971	-0.141
S5	-0.0132	-0.018	0.895	-0.0477	-0.367	-0.105	-0.622	-0.191	-3.29	-6.02	8.11	-0.633	-2.41	-0.96	-5.16	-2.3

SIZE PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.752 Prob. = 0.386

SIZE PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 5.988 Prob. = 0.014

SIZE PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 28.495 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 3.304 Prob. = 0.069

SIZE PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.156 Prob. = 0.693

SIZE PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.987 Prob. = 0.321

SIZE PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 19.061 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 7.882 Prob. = 0.005

USA Coefficients and T-Stats for Model 8 (BM sort):

r=a+b*ln(BM)+c*RMO+d*RMO*ln(BM)+e*SMB+f*SMB*ln(BM)+g*HML+h*HML*ln(BM)+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
B1	-0.0356	-0.0222	1.35	0.226	-1.3	-0.526	-1.54	-0.487	-4.33	-5.07	6.26	2.15	-4	-3.21	-6.17	-3.93
B2	0.0022	-0.00836	0.747	-0.152	-0.00731	0.0445	0.286	0.448	0.224	-1.13	2.65	-0.775	-0.0179	0.149	0.878	1.92
B3	-0.0044	-0.0215	0.487	-0.411	-0.466	-0.913	-0.145	-0.136	-0.382	-1.77	1.51	-1.3	-1.03	-1.92	-0.36	-0.319
B4	0.0145	0.000759	0.225	-1.02	0.892	0.802	-0.03	-0.00196	1.2	0.0475	0.906	-3.22	2.2	1.48	-0.083	-0.00406
B5	0.0203	0.0211	1.28	0.465	-0.647	-1.34	-0.0473	0.142	3.32	1.85	12.7	2.36	-3.58	-3.78	-0.34	0.482

BM PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.018 Prob. = 0.893

BM PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 1.317 Prob. = 0.251

BM PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 55.879 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 2.476 Prob. = 0.116

BM PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 3.473 Prob. = 0.062

BM PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 4.315 Prob. = 0.038

BM PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 4.508 Prob. = 0.034

BM PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.002 Prob. = 0.965

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20.2. UK. Not feasible due to the incapacity of LSUR application to complex matrices - Forthcoming correction and commentary from author.

CH Coefficients and T-Stats for Model 8 (Size sort):

r=a+b*ln(BM)+c*RMO+d*RMO*ln(BM)+e*SMB+f*SMB*ln(BM)+g*HML+h*HML*ln(BM)+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
S1	0.0355	-0.0257	0.895	-0.145	0.0697	0.238	0.161	0.324	2.12	-1.54	2.15	-0.335	0.144	0.485	0.341	0.653
S2	0.0179	-0.00798	0.739	-0.0252	0.592	-0.691	0.548	0.516	3.02	-0.551	5.94	-0.081	3.47	-1.6	3.63	1.13
S3	0.0149	-0.00997	0.64	-0.138	0.17	0.0549	0.436	-0.262	3.52	-1.35	7.06	-0.83	1.47	0.26	4.17	-1.23
S4	0.0205	-0.0141	0.654	-0.042	0.0584	0.0704	0.589	-0.142	5	-1.84	7.53	-0.253	0.507	0.341	5.33	-0.65
S5	0.0104	-0.00346	0.634	-0.083	-0.408	0.0897	0.106	-0.0888	3.21	-0.937	8.64	-0.917	-4.31	0.872	1.07	-0.847

SIZE PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 18.181 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 3.564 Prob. = 0.059

SIZE PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 43.512 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 0.296 Prob. = 0.586

SIZE PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 0.538 Prob. = 0.463

SIZE PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 0.059 Prob. = 0.807

SIZE PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 8.790 Prob. = 0.003

SIZE PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 0.122 Prob. = 0.727

CH Coefficients and T-Stats for Model 8 (BM sort):

r=a+b*ln(BM)+c*RMO+d*RMO*ln(BM)+e*SMB+f*SMB*ln(BM)+g*HML+h*HML*ln(BM)+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
B1	0.00448	-0.0073	0.663	-0.0164	-0.497	-0.0289	0.12	0.0322	1.08	-2.01	6.78	-0.188	-4.03	-0.269	0.881	0.273
B2	0.00908	-0.0147	0.706	-0.114	-0.417	0.151	0.475	0.0533	1.79	-1.82	6.37	-0.623	-2.77	0.673	3.12	0.243
B3	0.0236	-0.019	0.656	0.0968	0.133	-0.1	0.635	0.0151	4.76	-2.91	6.25	0.651	0.979	-0.562	5.14	0.0827
B4	0.00729	0.0124	0.403	0.39	0.0206	-0.373	0.543	-0.469	1.2	0.924	3.16	1.32	0.124	-0.991	3.63	-1.16
B5	0.0235	-0.0117	0.672	0.175	0.813	-0.659	-0.31	1.15	1.69	-0.765	1.82	0.408	1.89	-1.34	-0.741	2.34

BM PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 10.782 Prob. = 0.001

BM PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 2.212 Prob. = 0.137

BM PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 39.640 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.553 Prob. = 0.457

BM PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.008 Prob. = 0.930

BM PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 1.434 Prob. = 0.231

BM PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 6.584 Prob. = 0.010

BM PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.842 Prob. = 0.359

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21 Appendix XIII: Coefficients of Skewness Conditioned Three Factor in LSUR

21.1 USA

USA Coefficients and T-Stats for Model 9 (Size sort):
r=a+b*SKEW+c*RMO+d*RMO*SKEW+e*SMB+f*SMB*SKEW+g*HML+h*HML*SKEW+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
S1	0.00523	0.00642	0.944	-0.449	0.79	-0.67	-0.387	-0.111	1.67	0.82	15.6	-1.01	7.28	-1.16	-4.88	-0.828
S2	0.0121	0.00207	0.947	-0.125	0.695	-0.163	-0.271	-0.0195	5.09	1.96	20.3	-1.96	8.26	-1.73	-4.48	-0.843
S3	0.0113	0.00122	0.804	-0.0622	0.412	-0.113	-0.211	-0.00855	4.98	0.806	18.1	-0.623	5.08	-0.949	-3.66	-0.283
S4	0.0116	0.000318	0.928	-0.0311	0.151	-0.0166	-0.282	0.000424	6.95	0.74	29.4	-1.53	2.62	-0.772	-6.73	0.0455
S5	0.0116	-0.000977	0.959	0.0193	-0.184	-0.0305	-0.352	-0.025	12.1	-1.58	52.7	0.898	-5.45	-1.08	-15	-1.74

SIZE PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 51.850 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 1.056 Prob. = 0.304

SIZE PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 1068.101 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 1.657 Prob. = 0.198

SIZE PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 55.252 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 2.352 Prob. = 0.125

SIZE PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 67.837 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 1.115 Prob. = 0.291

USA Coefficients and T-Stats for Model 9 (B/M sort):

r=a+b*SKEW+c*RMO+d*RMO*SKEW+e*SMB+f*SMB*SKEW+g*HML+h*HML*SKEW+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
B1	0.00895	-0.00332	0.873	0.0853	-0.169	-0.072	-0.504	-0.0752	4.21	-1.93	21.1	1.55	-2.23	-0.874	-9.56	-1.7
B2	0.013	0.000339	0.984	-0.0242	-0.0781	-0.0113	-0.369	0.00145	6.49	0.699	26	-1.49	-1.14	-0.675	-7.5	0.143
B3	0.0169	0.00118	0.912	-0.117	0.449	-0.0413	-0.0224	0.0235	7.14	0.563	20.3	-1.14	5.44	-0.351	-0.379	0.445
B4	0.0149	0.00108	1.03	-0.0815	0.289	-0.0709	-0.0486	-0.00652	7.08	0.942	24.7	-1	3.73	-0.615	-0.901	-0.227
B5	0.00733	-0.000528	1.04	0.0183	-0.0622	0.106	-0.173	0.0263	2.47	-0.338	18.6	0.236	-0.605	0.911	-2.32	0.648

BM PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 164.919 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.146 Prob. = 0.702

BM PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 2815.487 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.518 Prob. = 0.472

BM PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 6.522 Prob. = 0.011

BM PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.162 Prob. = 0.688

BM PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 87.728 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.134 Prob. = 0.715

UK Coefficients and T-Stats for Model 9 (Size sort):

r=a+b*SKEW+c*RMO+d*RMO*SKEW+e*SMB+f*SMB*SKEW+g*HML+h*HML*SKEW+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
S1	0.00917	0.0215	0.614	0.353	0.737	0.295	0.066	-0.652	1.83	2.14	5.2	1.28	6.74	0.849	0.535	-2.02
S2	0.0123	0.00593	0.715	-0.124	0.634	-0.0722	0.235	0.051	3.41	1.25	8.38	-1.84	7.93	-0.458	2.77	0.388
S3	0.0143	0.0162	0.786	-0.271	0.536	-0.284	0.379	-0.122	3.24	1.81	7.49	-1.05	5.56	-0.726	3.64	-0.438
S4	0.00988	0.0147	0.877	-0.193	0.193	-0.191	0.259	0.0165	2.63	3.92	9.85	-1.62	2.35	-1.59	2.92	0.156
S5	0.0169	0.00298	0.717	-0.139	-0.363	0.0123	0.414	-0.106	6.19	2.24	10.9	-2.65	-5.92	0.194	6.37	-1.86

SIZE PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 15.788 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 12.760 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 94.833 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.566 Prob. = 0.452

SIZE PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 24.403 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 0.133 Prob. = 0.716

SIZE PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 12.808 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 2.226 Prob. = 0.136

UK Coefficients and T-Stats for Model 9 (B/M sort):

r=a+b*SKEW+c*RMO+d*RMO*SKEW+e*SMB+f*SMB*SKEW+g*HML+h*HML*SKEW+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
B1	0.0125	0.00187	0.702	-0.0611	-0.227	-0.0121	0.168	-0.0185	3.75	0.962	8.94	-1.41	-3.1	-0.21	2.15	-0.381
B2	0.017	0.0104	0.689	-0.128	-0.0857	-0.131	0.418	-0.306	4.75	2.87	8.22	-2.25	-1.11	-1.31	4.94	-2.26
B3	0.0199	0.0193	0.679	-0.226	-0.202	0.267	0.645	-0.765	4.82	2.14	7.24	-1.11	-2.27	0.947	6.72	-2.58
B4	0.0105	0.0101	0.737	-0.0961	-0.211	0.0979	0.426	-0.323	2.41	2.21	7.21	-0.669	-2.18	0.73	4.22	-2.23
B5	0.00973	0.01	0.847	-0.167	-0.432	0.464	0.425	-0.471	1.81	2.03	7.08	-1.27	-3.75	2.17	3.38	-2.57

BM PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 24.305 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 15.878 Prob. = 0.000

BM PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 118.369 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 4.722 Prob. = 0.030

BM PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 13.591 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 2.690 Prob. = 0.101

BM PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 38.537 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————————
Wald Chi-SQ(1) statistic = 18.090 Prob. = 0.000

CH Coefficients and T-Stats for Model 9 (Size sort):

r=a+b*SKEW+c*RMO+d*RMO*SKEW+e*SMB+f*SMB*SKEW+g*HML+h*HML*SKEW+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
S1	0.00825	0.0346	0.773	0.0791	0.337	0.507	0.527	-0.422	1.46	1.69	6.39	0.318	2.18	0.859	3.78	-0.859
S2	0.0107	0.012	0.758	-0.0781	0.336	-0.0102	0.538	0.0464	2.12	2.17	7.16	-1	2.4	-0.0963	4.06	0.403
S3	0.00924	0.0155	0.539	0.141	0.164	-0.0947	0.41	0.0457	2.31	1.75	6.61	0.849	1.53	-0.386	4.12	0.22
S4	0.0157	0.00436	0.694	-0.063	-0.0464	0.051	0.651	-0.0496	3.72	3.14	7.9	-2.5	-0.395	1.65	6.03	-1.71
S5	0.0109	0.000169	0.667	-0.0174	-0.477	0.000736	0.189	-0.0863	3.62	0.081	10.5	-0.488	-5.83	0.00993	2.48	-1.3

SIZE PORTFOLIOS - TEST OF CONSTANTS
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 12.263 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 7.659 Prob. = 0.006

SIZE PORTFOLIOS - TEST OF RMO ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 110.407 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*RMO COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 0.033 Prob. = 0.855

SIZE PORTFOLIOS - TEST OF SMB ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 0.537 Prob. = 0.464

SIZE PORTFOLIOS - TEST OF BM*SMB COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 0.441 Prob. = 0.506

SIZE PORTFOLIOS - TEST OF HML ALONE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 33.533 Prob. = 0.000

SIZE PORTFOLIOS - TEST OF BM*HML COMPOSITE
—— LSUR: Results for Linear Hypothesis Testing ——————
Wald Chi-SQ(1) statistic = 0.604 Prob. = 0.437

CH Coefficients and T-Stats for Model 9 (B/M sort):

r=a+b*SKEW+c*RMO+d*RMO*SKEW+e*SMB+f*SMB*SKEW+g*HML+h*HML*SKEW+u

	a	b	c	d	e	f	g	h	t(a)	t(b)	t(c)	t(d)	t(e)	t(f)	t(g)	t(h)
B1	0.00666	0.0049	0.624	0.0552	-0.53	0.065	0.0834	-0.089	1.87	1.32	8.3	0.676	-5.46	0.47	0.924	-0.922
B2	0.0122	0.00509	0.776	-0.125	-0.437	-0.035	0.406	-0.0199	2.88	1.87	8.7	-1.84	-3.74	-0.479	3.74	-0.158
B3	0.0155	0.00449	0.71	-0.0785	0.0075	0.0623	0.633	-0.0474	3.16	2.8	7.05	-2.43	0.0543	1.63	5.1	-1.47
B4	0.00736	0.00784	0.546	-0.0512	-0.141	0.0723	0.387	-0.0627	1.51	1.8	5.58	-0.784	-1.08	0.688	3.2	-0.54
B5	0.0108	0.00778	0.867	-0.133	0.267	0.065	0.579	0.0946	2.23	1.54	8.22	-1.14	1.91	0.518	4.54	0.997

BM PORTFOLIOS - TEST OF CONSTANTS
— LSUR: Results for Linear Hypothesis Testing —
Wald Chi-SQ(1) statistic = 12.953 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM ALONE
— LSUR: Results for Linear Hypothesis Testing —
Wald Chi-SQ(1) statistic = 11.971 Prob. = 0.001

BM PORTFOLIOS - TEST OF RMO ALONE
— LSUR: Results for Linear Hypothesis Testing —
Wald Chi-SQ(1) statistic = 133.710 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*RMO COMPOSITE
— LSUR: Results for Linear Hypothesis Testing —
Wald Chi-SQ(1) statistic = 3.118 Prob. = 0.077

BM PORTFOLIOS - TEST OF SMB ALONE
— LSUR: Results for Linear Hypothesis Testing —
Wald Chi-SQ(1) statistic = 4.248 Prob. = 0.039

BM PORTFOLIOS - TEST OF BM*SMB COMPOSITE
— LSUR: Results for Linear Hypothesis Testing —
Wald Chi-SQ(1) statistic = 0.857 Prob. = 0.355

BM PORTFOLIOS - TEST OF HML ALONE
— LSUR: Results for Linear Hypothesis Testing —
Wald Chi-SQ(1) statistic = 31.258 Prob. = 0.000

BM PORTFOLIOS - TEST OF BM*HML COMPOSITE
— LSUR: Results for Linear Hypothesis Testing —
Wald Chi-SQ(1) statistic = 0.285 Prob. = 0.594

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22. Appendix XIV: Programming Code for conditional skewness

```
for i(1,r,1);
   y=mbr[i,2*e-1:3*(e-1)-1];
   b=y'/x;
   resid=y'-x*b;
   emsqr=(ermsci-meanc(ermsci))'(ermsci-meanc(ermsci));
   eremsqr=sumc(resid.*emsqr);
   ersqr=resid'resid;
   eremsqr=eremsqr/r;
   ersqr=ersqr/r;
   emsqr=emsqr/r;
   coskew=coskew|eremsqr/sqrt(ersqr)*emsqr;
   endfor;
```