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VALUE VERSUS GROWTH

ΛΥΚΟΤΡΑΦΙΤΗ ΑΝΑΣΤΑΣΙΑ
ΕΠΙΒΛΕΠΩΝ:
ΚΑΘΗΓΗΤΗΣ
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VALUE VERSUS GROWTH

A large body of literature –starting with the classical paper by Fama and French has found evidence that value and growth factors are important in determining the cross section of expected equity returns, over and above systematic market risk.

This project aims at investigating the implications of this finding for optimal asset allocation .In particular we aim at assessing the role of value stocks and growth stocks in enhancing the return-risk trade –off of a stock market investor.

If value and growth are important determinants of an optimal stock portfolio, then portfolios including such stocks should systematically over perform the market index. Consequently, we will test the performance of value and growth portfolios using tests for intersection and spanning.

VALUE VERSUS GROWTH

Ένας μεγάλος όγκος της βιβλιογραφίας –αρχίζοντας από το κλασσικό έγγραφο από Fama και French έχει βρεί τα στοιχεία ότι οι παράγοντες VALUE and GROWTH είναι σημαντικοί στον καθορισμό του cross section of expected equity returns , επιπλέον του συστηματικού κινδύνου αγοράς.

Αυτό το πρόγραμμα στοχεύει στην έρευνα των επιπτώσεων αυτής της εύρεσης για το βέλτιστο asset allocation. Ιδιαίτερα στοχεύουμε στην αξιολόγηση του ρόλου VALUE and GROWTH στην ενίσχυση return-risk trade –off ενός επενδυτή χρηματιστηρίου.

Εάν η VALUE and GROWTH είναι σημαντικοί καθοριστικοί παράγοντες ενός βέλτιστου χαρτοφυλακίου μετοχών, κατόπιν τα χαρτοφυλάκια συμπεριλαμβανομένων τέτοιων μετοχών πρέπει συστηματικά να υπερβούν σε απόδοση το δείκτη αγοράς. Συνεπώς, θα εξετάσουμε την απόδοση των χαρτοφυλακίων VALUE and GROWTH χρησιμοποιώντας τις δοκιμές με intersection and spanning .

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INTRODUCTION

A large body of literature starting with the classical paper of Fama and French (1992) has found evidence that value and growth factors are important in determining the cross section of expected equity returns, over and above systematic market risk.

Common stocks are often divided into two categories

- Growth stocks sometimes called glamour stocks and
- Value stocks

Although there are no hard and fast rules on how they are divided, and disagreement exists among investment professionals on what category certain stock belong to.

A financial measure is often used to distinguish growth stocks from value stocks.

This is the book to market value (BV/MV). Growth stocks tend to have low (BV/MV) ratios and value stocks tend to have high (BV/MV) ratios

Other papers mentioned that there is also "size effect " in the stock market.

After that in this paper we will examine the role of value stocks, growth stocks, small size stocks and big size stocks in enhancing the return –risk trade –off of a stock market investor.

If value and growth are important determinants of an optimal stock portfolio, then portfolios including such stocks should systematically over perform the market index. Consequently, we will test the performance of value and growth portfolios using tests for intersection and spanning.

PORTFOLIO THEORY

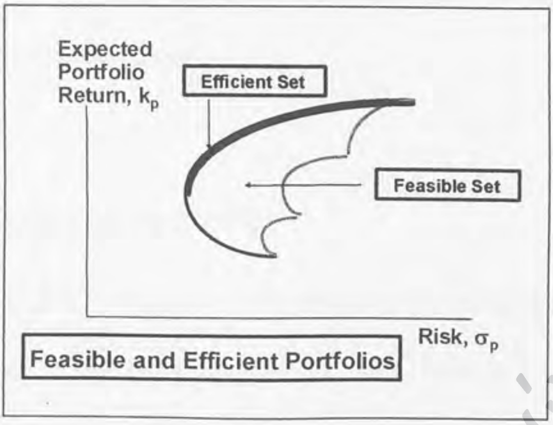
- **CAPM**

The CAPM is an equilibrium model that specifies the relation ship between risk and required rate of return for assets held in well-diversified portfolios. It is based that only one factor affects risk. The assumptions behind the CAPM are

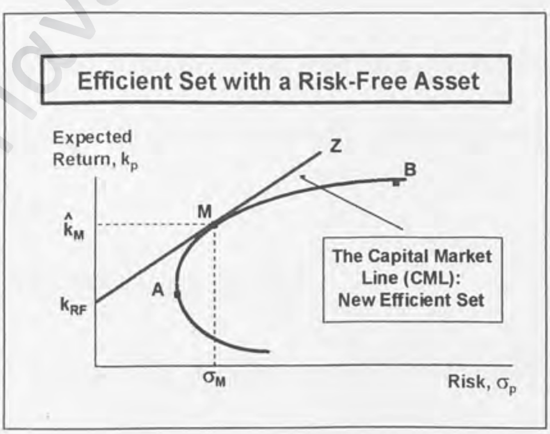
1. Investors all think in terms of a single holding period
2. All investors have identical expectations. Between two portfolios with identical standard deviations, they will choose the one with the higher expected return.
3. Investors can borrow or lend unlimited amounts at the risk-free rate.
4. All assets are perfectly divisible
5. There are no taxes and no transactions costs
6. Investors are risk averse so when given a choice between two portfolios with identical expected returns, they will choose the one with the lower standard deviation. Information is friendly and instantly available to all investors.

In the world of the CAPM it is a simple matter to determine the relation ship between risk and expected return for efficient portfolios. **Efficient portfolios** is the one that offers:

1. The most return for a given amount of risk or
2. The least risk for a give amount of return



The collection of efficient portfolios is called the **efficient set** or **efficient frontier.** The linear efficient set of the CAPM is known as the **Capital Marker Line (CML).** All portfolios other than those employing the market portfolio and risk free borrowing or lending would lie below the CML, although some might plot very close to it. The CAPM tell us that the expected rate of return on any efficient portfolio is equal to the risk-free rate plus a risk premium, and the optimal portfolio for any investor is the point of tangency between the CML and the investor's indifference curves. The **CML** gives the risk/return relationship for the **efficient portfolios**.



The **Security Market Line (SML)**, also part of the **CAPM**, gives the risk/return relationship for **individual stocks.**

Are there problems with the CAPM?

CAPM/SML concepts are based on expectations, yet betas are calculated using historical data. A company's historical data may not reflect investors' expectations about future risk ness. Other models are being developed that will one day replace the CAPM, but it still provides a good framework for thinking about risk and return

- **Arbitrage Pricing Theory (APT)**The CAPM is a single factor model. The

APT proposes that the relationship between risk and return is more complex and may be due to multiple factors such as GDP growth, expected inflation, tax rate changes, and dividend yield. Then if two stocks had the same market risk the stock paying the higher dividend would have the higher required rate of return .In that case, required returns would be a function of two factors, market risk and dividend policy. The **APT** can include any number of risk factors, so the required return could be a function of two, three, four, or more factors. Also although the **APT** model is widely discussed in academic literature, practical usage to date has been limited.

Required Return for Stock under the APT

$k_i = k_{RF} + (k_1 - k_{RF})b_1 + (k_2 - k_{RF})b_2 + ... + (k_j - k_{RF})b_j.$

k_j = required rate of return on a portfolio sensitive only to economic Factor j.

b_j = sensitivity of Stock i to economic factor j.

The primary theoretical advantage of the APT is that it is being used for some real world applications. However the APT faces several major hurdles in implementation, the most severe being that the APT does not identify the relevant factors. Thus APT does not tell us what factors influence returns, nor does it even indicate how many factors should appear in the model. More research on risk and return models is needed to find a model that is theoretically sound, empirically verified, and easy to use.

- **The Fama French three factor model**

The results of two studies by Eugene Fama and Kenneth French of the university of Chicago seriously challenge the CAPM. In the first of these papers, published in 1992 Fama and French hypothesized that the SML should have three factors. **The first** is **the stock's CAPM beta**, which measures the market risk of the stock .**the second** is the **size** of the company, measured by the **market value** of its equity (market evaluation), because if small companies are riskier than large companies, then we might expect small companies to have higher stock returns than large companies. The third factor is the book value of equity divided by the market value of equity, or the book to market ratio (B/M). If the market value is larger than the book value, the investors are optimistic about the stock future .On the other hand, if the book value is larger than the market value, then investors are pessimistic about the stock's future, and it is likely that that a ratio analysis would reveal that the company is experiencing sub –par operating performance and possibly even financial distress. In other words, a stock with a high B/M ratio might be risky, in which case investors would require a higher expected return to induce them to invest in such a stock.

When Fama and French tested their hypotheses, they found that small companies and companies with high B/M ratios had higher rates of return than the average stock, just as they hypothesized. Somewhat surprisingly, however, they found no relation between beta and return. After taking into account the returns due to the company's size and B/M ratio, high beta stocks did not have higher –than- average returns, and low beta stocks did not have lower -than - average returns. In the second of their two studies, published in 1993,Fama and French developed a three factor model based on their previous results .The first factor in the **Fama French three factor model** is the market risk premium, which is the marker return km,minus the risk free Krf.Thus their model begins like CAPM ,but they go on to add a second and third factor .To form the second factor ,they ranked all actively traded stocks by size and then divided them into two portfolios ,consisting of small and bid stocks. They calculated the return on each of these two portfolios, and created a third one by subtracting the return from the big portfolio from that of the small one. They called this the **SMB** portfolio (for small size minus big size). This portfolio is designed to measure the variation in stock returns that is caused by the size effect .To form the third portfolio; they ranked all stocks according to their book to marker ratios (B/M). They placed the 30% of stocks with the highest ratios into a portfolio that they called the H portfolio (for high B/M ratios). They placed the 30% of stocks with the lowest ratios into a portfolio called the L portfolio (for low B/M ratios). They subtracted the return of the L portfolio from the H portfolio, and they called the result the **HML** portfolio (for high B/M ratio minus the low B/M ratio)

$k_i = k_{RF} + (k_M - k_{RF})b_i + (k_{SMB})c_i + (k_{HMB})d_i$,

b_i = sensitivity of Stock i to the market return.

c_j = sensitivity of Stock i to the size factor.

d_j = sensitivity of Stock i to the book-to-market factor.

To date the Fama and French three-factor model has been used primarily by academic researchers rather than managers at actual companies, the majority of whom is using CAPM .One reason for this difference is data availability. Most professors have access to the type of data that is required to calculate the factors, but the data for the size factor and the B/M factor are not readily available to the general public.A second reason is the difficulty in estimating the expected values of the size factor and the B/M factor. Although we know the historical average returns for these factors, we do not know whether the past historical returns are good estimators of the future expected returns. Third many managers choose to wait and adopt a new theory only after the new theory has been widely accepted by the academic community.

LITERATURE REVIEW

Fama and French (1992)-cross section of expected stock return and common risk factors in the returns on stocks and bonds

The asset pricing model of Sharpe (1964),Linter(1965)and Black (1972)has long shaped the way academics and practitioners think about average returns and risk, The central prediction of the model is that the market portfolio of invested wealth is mean variance efficient in the sense of Markowitz(1959)The efficiency of the market portfolio implies that a)expected returns on securities are a positive linear function of their market betas (the slope in the regression of a security 's return on the market's return) and b) market betas suffice to describe the cross section of expected returns .

There are several contradictions of the SLB model. Some of them are : **Banz** (1981) he finds that market equity (ME) adds to the explanation of the cross section of average returns provided by market betas .Average returns on small –with low ME –stocks are too high given their beta and Average returns on large stocks –with high ME –are too low , Then **Bhandari** (1988) documented that there is a positive relation between leverage and average return ,and he added that leverage return helps explain the cross section of average stock returns in tests that include size (ME) as well as beta ,**Stattman** (1980) and **Rosenberg ,Reid ,Lanstein** (1985)find that average return on U,S, stocks are positively related to the ratio of a firm's book value of common equity (BE), to its market value (ME),**Chan,Hamao** and **Lakonishok** (1991) find that book to market equity (BE / ME) also has a strong role in explaining the cross section of average returns in Japanese stocks,Finally Basu(1983) showed that earnings price ratios (p/e) help explain the cross section of average returns on U,S stocks in tests that also includes size and market beta ,Variables like size ,E/P, leverage and book to market equity(BE/ME) as reported from previous studies are all scaled versionsof a firm's stock price , They can be regarded as different ways for extracting information from stock prices about the cross section of expected stock returns **(Ball 1978)(KEIM 1988),**Since all these variables are scaled versions of price it is reasonable to expect that some of them are redundant for explaining average returns ,.The tests of Black , Jensen and Mac Beth(1973) find that as predicted from the SLB model there is a positive simple relation between average stock returns and beta through the pre-1969 period ,SLB model in accordance with Reinganum (1981)and Lakonishok and Shapiro (1986) find that the relation between beta and average return disappears during the most recent 1963-1990 period even when beta is used alone to explain average returns But they also find that the simple relation between beta and average return is also weak in the 1941-1990 recent period ,**That means that several tests do not support the idea of the SLB model that average stock returns are positively related to market b.**

These tests also conclude that two easily variables size and book to market equity, seem to describe the cross section of average stock returns, Prescriptions for using this evidence depend on a) whether it will persist and b) whether it results from rational or irrational asset pricing.

Fama and French (1992)- five common risk factors in the returns on stocks and bonds

Another paper of Fama and French identifies five common risk factors in the returns on stocks and bonds. There are three stock market factors: an overall market factor and factors related to firm size and book to market equity and two bond market factors related to maturity and default risk. The list of empirically determined average return variables includes size(ME ,stock price times number of shares),leverage ,earnings /price (E/P),and book to marker equity(the ratio of the book value of a firm' s common stock, BE ,to its market value ,ME). Fama and French study the joint roles of market b, size, E/P, leverage, and book to market equity in the cross section of average stock return. They found that used alone or in combination with other variables, b, (the slope in the regression of a security 's return on the market's return) has little information about average returns. Used alone size, E/P, leverage, and book to market equity have explanatory power. In combinations, size (ME) and book to market equity (BE/ME) seem to absorb the apparent roles of leverage and E/P in average returns. The bottom line result is that two empirically determined variables size and book to market equity, do a good job explaining the cross section of average stock returns. Another evidence that size and book to market equity indeed proxy for sensitivity to common risk factors in stock returns, is that portfolios constructed to mimic risk factors related to size and BE/ME capture strong common variation in returns, no matter what else is in the time series regressions.

Although size and book to market equity seem like ad hoc variables for explaining average stock returns, we have reason to expect that they proxy for common risk factors in returns. Fama and French document that size and book to market equity are related to economic fundamentals Not surprisingly, firms that have high BE/ME (a low stock price relative to book value) tend to have low earnings on asset. Conversely, low BE/ME (a high stock price relative to book value) is associated with persistently high earnings. Size is also related to profitability. Controlling for book to market equity small firms tend to have lower earnings on assets than big firms. The fact that small firm can suffer a long earnings depression that bypasses big firms suggests that size is associated with a common risk factor that might explain that negative relation between size and average return. Similarly the relation between book to market equity and earnings suggests that relative profitability is the source of a common risk factor in returns that might explain the positive relation between BE/ME and average return. One of the major tasks for Fama and French is to measure the common variation in returns associated with the size and BE/ME. Fama and French have decided to sort firms into some groups following the evidence that book to market equity has a stronger role in average stock returns than size. We construct six portfolios (S/L,S/M,S/H,B/L,B/M,B/H) from the intersection of the two ME and the three BE/ME groups. After all they construct

1. the **SMB (small minus big)** portfolio.This portfolio meant to mimic the risk factor in returns related to size, and is the difference each month between the simple average of the returns on the three small stock portfolios (S/L,S/M, and S/H)and the simple average of the returns on the three big portfolios (B/L,B/M, and B/H).Thus ,SMB **is the difference between the returns on small and big stock portfolios with about the same weighted average book to market equity.** This difference should be largely free from the influence of BE/ME focusing instead on the different return behaviors of small and big stocks.

2. The **HML (high minus low)** portfolio. This portfolio meant to mimic the risk factor in returns related to book to market equity. HML is the difference, each month, between the simple average of the returns on the two high BE/ME portfolios (S/H and B/H) and the average of the returns n the two low BE/ME portfolios (S/L and B/L). The two components of HML are returns on high and low BE/ME portfolios with about the same weighted average size. Thus the difference between the two returns should be

largely free of the size factor in returns, focusing instead on the different return behaviors of high and low BE/ME firms.

In September 1992 Fama and French check the robustness of the inference that five common risk factors explain the cross section of expected stock returns. Roll (1983) and Keim (1983) documenting that stock returns, especially returns on small stocks, tend to be higher in January it is standard in tests to look for unexplained January effects. Despite the fears, we notice that the January seasonal in the returns on stocks is weak at best.

Fama and French- (1995)-size and book to market factors in earnings and returns

The long-term goal in this article is to provide an economic foundation for the empirical relations between average stock return and size, and average return and book to market equity. The work till now has showed that if

1. Average return relations are due to rational pricing, then there must be common risk factors in returns associated with size and BE/ME and
2. The size and book to market patterns in returns must be explained by the behavior of earnings.

The authors have proved that size and BE/ME proxy for sensitivity to risk factors that capture strong common variation in stock returns and help explain the cross section of average return .The methodology presented shows that size and BE/ME are related to profitability.

In a rational market, short-term variation in profitability should have little effect on stock price and book to market equity. BE/ME should be associated with long term differences in profitability .Our results confirm this prediction. Firms with high BE/ME (a low stock price relative to book value) tend to be persistently distressed. They have low ratios of earnings to book equity for at least 11 years around portfolio formation. Conversely, low BE/ME (a high stock price relative to book value) is associated with sustained strong profitability. Within book to market groups, small stocks tend to be less profitable than big stocks.

The relation between size and profitability is however, largely to the 1980s. Prior to 1980s given BE/ME ratios of earnings to book equity are similar for small and big stocks. But for small stocks the recession of 1981 and 1982 turns into a prolonged earnings depression. On average small stocks do not participate in the boom of the middle and late 1980s.Though we have no explanation for the small stocks depression of the 1980s,it does suggest that there is a size factor in fundamentals that might lead a size related risk factor in returns.

We find that there are size and book to market factors that in earnings like those in returns. The earnings of firms in different size BE/ME groups load on market, size and BE/ME factors in earnings in much the same way that their stock returns load on the corresponding common factors in returns.

The effort of Fama and French to prove that the common variation in returns is driven by the common factors in earnings is not entirely successful.

They found that the market and size factors in earnings help explain the market and size factors in returns. But they found no evidence that returns respond to the book to market factor in earnings.

Multifactor Explanation of Asset Pricing Anomalies (1996)

Previous work shows that average returns on common stocks are related to firm characteristics like size, earnings/price, cash flow/price, book-to-market equity, past sales growth, long-term past return, and short-term past return. Because these patterns in average returns apparently are not explained by the CAPM, they are called anomalies. We find that, except for the continuation of short-term returns, the anomalies largely disappear in a three-factor model. The results are consistent with rational ICAPM or APT asset pricing, but they also consider irrational pricing and data problems as possible explanations.

Researchers have identified many patterns in average stock returns. For example, DeBondt and Thaler (1985) find a reversal in long-term returns. Stocks with low long-term past returns tend to have higher future returns. In contrast, Jegadeesh and Titman (1993) find that short-term returns tend to continue. Stocks with higher returns in the previous twelve months tend to have higher future returns. Others show that a firm's average stock return is related to its size (ME, stock price times number of shares), book-to-market-equity (BE/ME, the ratio of the book value of common equity to its market value), earnings/price (E/P), cash flow/price (C/P), and past sales growth (Banz (1981), Basu (1983), Rosenberg, Reid, and Lanstein (1985), and Lakonishok, Shleifer and Vishny (1994)). Because these patterns in average stock returns, which are not explained by the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), they are typically called anomalies.

This paper argues that many of the CAPM average-return anomalies are related, and they are captured by the three-factor model in Fama and French (FF 1993). The model says that the expected return on a portfolio in excess of the risk-free rate $[E(R_i) - R_f]$ is explained by the sensitivity of its return to three factors: (i) the excess return on a broad market portfolio $(R_M - R_f)$; (ii) the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB, small minus big); and (iii) the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks (HML, high minus low). Specifically, the expected excess return on portfolio i is,

$$E(R_i)- R_f = b_i[e(R_M) - R_f] + s_iE(SMB) + h_iE(HML), \quad (1)$$

Where $E(R_M) - R_f$, E(SMB), and E(HML) are expected premiums, and the factor sensitivities or loadings, b_i, s_i, and h_i, are the slopes in the time-series regression,

$$Ri-R_f = a_i + b_i(R_M-R_f) + s_i\, SMB + h_i\, HML + e_i$$

Fama and French (1995) show that book-to-market equity and slopes on HML, proxy for relative distress. Weak firms with persistently low earnings tend to have high BE/ME and positive slopes on HML; strong firms with persistently high earnings have to low BE/ME and negative slopes on HML.

At a minimum, the available evidence suggests that the three-factor model is a parsimonious description of returns and average returns. The model captures much of the variation in the cross-section of average stock returns, and it absorbs most of the anomalies that have plagued the CAPM. More aggressively, Fama and French supported (1993, 1994, 1995) that the empirical successes of (1) suggest that it is an equilibrium pricing model, a three-factor version of Merton's (1973) intertemporal CAPM (ICAPM) or Ross's (1976) arbitrage pricing theory (APT). In this view, SMB and HML mimic combinations of two underlying risk factors or state variables of special hedging concern to investors.

To set the stage, in a test on 25 Fama and French size BE /ME portfolios they consider the average excess returns on the 25 Fama-French (1993) size BE/ME portfolios of value-weighted NYSE, AMEX, and NASD stocks. The results shows that small stocks tend to have higher returns than big stocks and high-book-to-market stocks have higher returns than low-BE/ME stocks.

A comment on methodology is necessary. In the time-series regression, variation through time in the expected premiums $E(R_M)-R_f$, E(SMB), and E(HML) in (1) is embedded in the explanatory returns, RM-Rf, SMB, and HML. Thus the regression intercepts are net of variation in the expected premiums.

Lakonishok, Shleifer, and Vishny (LSV 1994) in a second test examined the returns on sets of deciles formed from sorts on BE/ME, E/P, C/P, and five-year sales rank. They produced strong positive relations between average return and BE/ME, E/P, or C/P, they found that past sales growth is negatively related to future return.

In another regression analysis they showed that higher-C/P portfolios produced larger slopes on SMB and especially HML. This pattern in the slopes is also observed for the BE/ME and E/P deciles. It seems that dividing an accounting variable by stock price produces a characterization of stocks that is related to their loadings on HML. Given the evidence in Fama and French (1995) that loading on HML proxy for relative distress, we can infer that low BE/ME, E/P, and C/P are typical of strong stocks, while high BE/ME, E/P, and C/P and typical of stocks that are relatively distressed.

Portfolios Formed on Past Returns

DeBondt and Thaler (1985) find that when portfolios are formed on long-term (three- to five-year) past returns, losers (low past returns) have high future returns and winners (high past returns) have low future returns. In contrast, Jegadeesh and Titman (1993) and Asness (1994) find that when portfolios are formed on short-term (up to a year of) past returns, past losers tend to be future losers and past winners are future winners.

Kothari (1989), Chopra, Lakonishok, and Ritter (1992), falls neatly within the predictions of our three-factor model. Moreover, since the model captures the economic essence of long-term winners (strong stocks) and losers (smaller distressed stocks), we speculate that it can explain the stronger reversal of long-term returns observed in a specific period.

Exploring Three-Factor Models

Many patterns in average stock returns, so-called anomalies of the CAPM, are captured by the three-factor model of (1). In this section they show that the explanatory returns of the model are not unique. Many other combinations of three portfolios describe returns as well as R_M - R_f, SMB, and HML. These results support our conclusion that a three-factor model is a good description of average returns.

They first provide some background. Fama (1994) shows that a generalized portfolio-efficiency concept drives Merton's (1973) ICAPM. Because ICAPM investors are risk averse, they are concerned with the mean and variance of their portfolio return. ICAPM investors are, however, also concerned with hedging more specific state-variable (consumption-investment) risks. As a result, optimal portfolios are multifactor-minimum-variance (MMV): they have the smallest possible return variances, given their expected returns and sensitivities to the state-variables.

The Case for a Multifactor ICAPM or APT

In FF (1992) they reject the CAPM based on evidence that size and book-to-market-equity (BE/ME) capture cross-sectional variation in average returns that is missed by univariate market βs. They have since tried to infer whether these size and book-to-market effects are generated by a multifactor ICAPM or APT.

One necessary condition for multifactor ICAPM or APT pricing is multiple common (undiversifiable) sources of variances in returns.FF (1993) show that there is indeed covariation in returns related to size and BE/ME (captured by loadings on SMB and HML), above and beyond the covariation explained by the market return. Moreover, FF (1995) show that there are common factors in fundamentals like earnings and sales that look a lot like the SMB and HML factors in returns.

The acid test of the three-factor model is whether it can explain differences in average returns. FF (1993) find that the model describes the average returns on portfolios like SMB and HML that are formed on size and BE/ME can explain the returns on other portfolios formed on size and BE/ME. They address this concern here by testing whether the three-factor model can explain other promiment CAPM average-return anomalies. They find that the patterns in average return produced by forming portfolios on E/P, C/P, sales growth, and long-term past return are absorbed by the three-factor model, largely because they line up with the loading of the portfolios on HML. The tests of (1) on industries in FF (1994) are also a check on FF (1993).

The three-factor model (1) is also useful in applications. For example, Reinganum (1990) finds that size-adjusted average returns are higher for NYSE stocks than for NASD stocks. Fama, French, Booth, and Sinquefield (1993) use (1) to explain this puzzling result. Controlling for size, NYSE stocks have higher loadings on HML, and thus higher predicted returns. Carhart (1994) finds that the three-factor model (1) provides sharper evaluations of the performance of mutual than the CAPM. SMB adds a lot to the description of the returns on small-stock funds, and loadings on

HML are important for describing the returns on growth-stock funds. FF (1994) find that the three-factor model (1) signals higher costs of equity for distressed industries than for strong industries, largely because the distressed industries have higher loadings on HML.

FF (1993) interpret the average HML return as a premium for a state-variable risk related to relative distress. This story is suggested by the evidence in FF (1995) that low book-to-market-equity is typical of firms that have persistently strong earnings, while high-BE/ME is associated with persistently low earnings. Moreover, FF (1994) argue that the variation through time in the loadings of industries on HML correctly reflects periods of industry strength or distress. Industries have strong positive HML loadings in bad times and negative loadings when times are good. Finally, Chan and Chen (1991) present evidence for a risk factor in returns and average returns related to relative-distress.

Why is relative distress a state variable of special hedging concern to investors? One possible explanation is linked to human capital, an important asset for most investors. Consider an investor with specialized human capital tied to a growth firm (or industry or technology). A negative shock to the firm's prospects probably does not reduce the value of the investor's human capital; it may just mean that employment in the firm will expand less rapidly. In contrast, a negative shock to a distressed firm more likely implies a negative shock to the value of specialized human capital since employment in the firm is more likely to contract. Thus, workers with specialized human capital in distressed firms have an incentive to avoid holding their firms' stocks. If variation in distress is correlated across, firms, workers in distressed firms have an incentive to avoid the stocks of all distressed firms. The result can be a state-variable risk premium in the expected returns of distressed stocks.

The Distress Premium Is Irrational

Lakonishok, Shleifer, and Vishny (LSV 1994), Haugen (1995), and MacKinlay (1995) argue that the premium for relative distress, the difference between the average returns on high- and low-book-to-market stocks, is too large to be explained by rational pricing. Indeed, LSV and Haugen conclude that the premium is almost always positive and so is close to an arbitrage opportunity. If the premium for relative distress is close to an arbitrage opportunity, the standard deviation of HML should be small.

The yearly returns confirm that a high-book-to-market strategy is not a sure thing.

But the fact that the premium for relative distress is not an arbitrage opportunity does not imply that it is rational. LSV and Haugen argue that the premium is due to investor over-reaction. Specifically, investors do not understand that the low earnings growth of high-BE/ME firms and the high earnings growth of low-BE/ME firms quickly revert to normal levels after portfolios are formed on BE/ME, FF (1995) argue, however, that over-reaction cannot be the whole story, since the high distress premium in returns persists for at least five years after portfolio formation, but the mean reversion of earnings growth is apparent much sooner.

Another LSV argument is that the relative-distress premium is irrational because periods of poor returns on distressed stocks are not typically periods of low GNP growth or low overall market returns. Since the relative-distress premium is not related to these obvious macroeconomic state variables, they conclude that the premium arises simply because investors dislike distressed stocks and so cause them to be under priced.

Finally, LSV argue that the relative distress premium is irrational because diversified portfolios of high- and low-book-to-market firms have similar return variances. Equation (1) provides an explanation. The positive HML slopes of high-BE/ME (distressed) firms raise their return variances and imply higher average returns.

Fama and French (1993) found that the three-factor-risk-return relation is a good model for the returns on portfolios formed on size and book-to-market-equity. They found that: (1) also the three-factor-risk-return relation explains the strong patterns in returns observed when portfolios are formed on earnings/price, cash flow/price, and sales growth, variables recommended by Lakonishok, Shleifer, and Vishny (1994) and others. The three-factor risk-return relation also captures the reversal of long-term returns documented by DeBondt and Thaler (1985). Thus, portfolios formed on E/P, C/P, sales growth, and long-term past returns do not uncover dimensions of risk and expected return beyond those required to explain the returns on portfolios formed on size and BE/ME. Fama and French (1994) extend this conclusion to industries.

The three-factor risk-return relation is, however, just a model. It surely does not explain expected returns on all securities and portfolios. They found that the three-facor-risk-return model couldn't explain the continuation of short-term returns documented by Jegadeesh and Titman (1993) and Asness (1994).

Finally, there is an important hole in their work. Their test to date do not cleanly identify the two consumption-investment state variables of special hedging concern to investors that would provide a neat interpretation of our results in terms of Merton's (1973) ICAPM or Ross' (1976) APT. The results of Chan and Chen (1991) and Fama and French (1994, 1995) suggest that one of the state variables is related to relative distress. But this issue is far from closed, and multiple competing interpretations of our results remain viable.

The Conditional CAPM and the Cross-Section of Expected Returns

Most empirical studies of the static CAPM assume that betas remain constant over time and that the return on the value-weighted portfolio of all stocks is a proxy for the return on aggregate wealth. The general consensus is that the static CAPM is unable to explain satisfactorily the cross-section of average returns on stocks. They assumed that the CAPM holds in a conditional sense. That means betas and the market risk premium vary over time. They included the return on human capital when measuring the return on aggregate wealth. Their specification performed well in explaining the cross-section of average returns.

A substantial part of the research effort in finance is directed toward improving our understanding of how investors value risky cash flows. It is generally agreed that investors demand a higher expected return for investment in riskier projects, or securities. However, They still do not fully understand how investors assess the risk of the cash flow on a project and how they determine what risk premium to demand. Several capital asset-pricing models have been suggested in the literature that describe how investors assess risk and value risky cash flows. Among them, the Sharpe-Lintner-Black Capital Asset Pricing Model (CAPM) is the one that financial managers use most often for assessing the risk of the cash flow from a project and for arriving at the appropriate discount rate to use in valuing the project. According to the CAPM, (a) the risk of a project is measured by the beta of the cash flow with respect to the return on the market portfolio of all assets in the economy, and (b) the relation between required expected return and beta is linear.

Over the past two decades a number of studies have empirically examined the performance of the static version of the CAPM in explaining the cross-section of realized average returns. The results reported in these studies support the view that it is possible to construct a set of portfolios such that the static CAPM is unable to explain the cross-sectional variation in average returns among them. In particular, portfolios containing stocks with relatively small capitalization appear to earn higher returns on average than those predicted by the CAPM.

In spite of the lack of empirical support, the CAPM is still the preferred model for classroom use in MBA and other managerial finance courses. In a way it reminds us of cartoon characters like Wile E. Coyote who have the ability to come back to original shape after being blown to pieces or hammered out of shape. Maybe the CAPM survives because (a) the empirical support for other asset-pricing models is no better, (b) the theory behind the CAPM has an intuitive appeal that other models lack, and (c) the economic importance of the empirical evidence against the CAPM reported in empirical studies is ambiguous.

In their widely cited study, Fama and French (1992) present evidence suggesting that the inability of the static CAPM to explain the cross-section of average returns that has been reported in the literature may be economically important. Using return data on a large collection of assets, they examine the static version of the CAPM and find that the "relation between market beta and average return is flat". The CAPM is widely viewed as one of the two or three major contributions of academic research to financial managers during the postwar era. As Fama and French point out, the robustness of the size effect and the absence of a relation between beta and average return are so contrary to the CAPM that they shake the foundations on which MBA and other managerial course materials in finance are built.

The CAPM was derived by examining the behavior of investors in a hypothetical model-economy in which they live for only one period. In the real world investors live for many periods. Therefore, in the empirical examination of the CAPM, using data from the real world, it is necessary to make certain assumptions. One of the commonly made assumptions is that the betas of the assets remain constant over time. In our view, this is not a particularly reasonable assumption since the relative risk of a firm's cash flow is likely to vary over the business cycle. During a recession, for example, financial leverage of firms in relatively poor shape may increase sharply relative to other firms, causing their stock betas to rise.

Also, so the extent that the business cycle in induced by technology or taste shocks, the relative share of different sectors in the economy fluctuates, inducing fluctuations in the betas of firms in these sectors. Hence, betas and expected returns will in general depend on the nature of the information available at any given point in time and vary over time. In this study, Fama and French assumed that the conditional version of the CAPM holds, i.e., the expected return on an asset based on the information available at any given point in time is linear in its conditional beta.

Though several researchers have empirically examined the conditional version of the CAPM, no one to our knowledge has directly studied the ability of the conditional CAPM to explain the cross-sectional variation in average returns on a large collection of stock portfolios. The focus of this paper is to fill this gap in the literature. For the purpose, They first derived the unconditional model implied by the conditional CAPM. They showed that when the conditional version of the CAPM holds (i.e., when betas and expected returns are allowed to vary over the business cycle), a two-factor model obtains unconditionally. Average returns are jointly linear in the average beta and in a measure of "beta instability". The fact that the implied unconditional model nests the static CAPM facilitates direct comparison of their relative performance.

The Sharpe-Lintner-Black (Static) CAPM

Let R_i denote the return on any asset I and R_m be the return on the market portfolio of all assets in the economy. The Black (1972) version of the CAPM is

$$E[R_i] = \gamma_o + \gamma_1\beta_i$$

where β_i is defined as

$$\beta_i = Cov(R_i, R_m)/Var[R_m],$$

and E[.] denoted the expectation, Cov(·) denoted the covariance, and Var[·] denotes the variances.

In their widely cited study, Fama and French (1992) empirically examine the CAPM given above and find that the estimated value of γ_1 is close to zero. They interpret the "flat" relation between average return and beta as strong evidence against the CAPM.

While a "flat" relation between average return (the sample analog of the unconditional expected return) and beta may be evidence against the static CAPM, it is not necessarily evidence against the conditional CAPM.

The CAPM was developed within the framework of a hypothetical single-period model economy. The real world, however, is dynamic and hence, as pointed out earlier, expected returns and betas are likely to vary over time. Even when expected returns are linear in betas for every time period, based on the information available at the time, the relation between the unconditional expected return and the unconditional beta could be "flat".

There are two major difficulties in examining the empirical support for the static CAPM.

(a) The real world is inherently dynamic and not static.

(b) The return on the portfolio of aggregate wealth is not observable. These issues are typically ignored in empirical studies of the CAPM. It is commonly assumed that betas of assets remain constant over time, and the return on stocks measures the return on the aggregate wealth portfolio. Under these assumptions, Fama and French (1992) find that the relation between average return and beta is flat and that there is a strong size effect.

Many researchers argued that those two assumptions are not reasonable. Relaxing the first assumption naturally leads us to examine the conditional CAPM. Thay demonstrated that the empirical support for our conditional CAPM specification is rather strong. When betas and expected returns are allowed to vary over time by assuming that the CAPM holds period by period, the size effects and the statistical rejections of the model specifications become much weaker. When a proxy for the return on human capital is also included in measuring the return on aggregate wealth, the pricing errors of the model are not significant at conventional levels. More importantly, firm size does not have any additional explanatory power.

Although the conditional model performs substantially better than the static model, They still advocate caution in interpreting these results as strong support for the conditional CAPM for the following reasons:

(a) In a dynamic world, investors may care about hedging against a variety of risks that do not arise in a static economy. One possibility is to extend Merton's inter-temporal CAPM for empirical analysis, along the lines suggested by Campbell .

However, the dynamic conditional CAPM has an undesirable feature. The econometrician has to take a stand on the nature of the information available to the investors. For example, while deriving the unconditional multi-factor model implied by the conditional CAPM, They assumed that the conditional market risk premium is a linear function of the yield spread between low- and high-grade bonds. An alternative is to follow Bansal, Hsieh, and Viswanathan (1993) and Bansal and Veiswanathan (1993) and consider unconditional nonlinear factor models which may be relatively more robust to information-set misspecification.

(b) A number of events occur at deterministic monthly and yearly frequencies. It may be reasonable to expect that such events may influence the behavior of asset prices at these frequencies. Since such events are outside the scope of asset-pricing models like the CAPM, one strategy would be to study the performance of models by using annual data over a sufficiently long period of time, as in Amihud, Christensen, and Mendelson (1992), Jagannathan and Wang (1992), and Kothari, Shanken, and Sloan (1995). Such an approach has its own shortcomings, the most important of which is that the economy may not really be stationary. There is some need for developing statistical sampling theories for making inferences that are robust to the presence of such features, possibly along the lines of Bossaerts (1994).

Finally, we have to keep in mind that the CAPM, like any other model, is only an approximation of reality. Hence, it would be rather surprising if it turns out to be "100 percent accurate". The interesting question is not whether a particular asset-pricing model can be rejected by the data. The question is: "How inaccurate is the model?" Fama and French (1992) show that the static version of the CAPM is very inaccurate. They found that the conditional version of the CAPM explains the cross-section of stock returns rather well. In doing so, they implicitly assumed that the portfolio of stocks used in their study is economically important.

The conditional CAPM we study in this article is very different from what is commonly understood as the CAPM, and resembles the multi-factor model of Ross (1976). The model they evaluated has three betas, whereas the standard CAPM has only one beta. They choused this model because (i) the use of a better proxy for the return on the market portfolio results in a two-beta model in place of the classical one-beta model, and (ii) when the CAPM holds in a conditional sense, unconditional expected returns will be linear in the unconditional beta as well as a measure of beta-instability over time. When the CAPM holds conditionally, we need more than the unconditional beta calculated by using the value-weighted stock index to explain the cross-section of unconditional expected returns.

Value versus Growth: The International Evidence

Value stocks have higher returns than growth stocks in markets around the world. An international capital asset pricing model cannot explain the value premium, but a two-factor model that includes a risk factor for relative distress captures the value premium in international returns.

Investment managers classify firms that have high ratios of book-to-market equity (B/M), earnings to price (E/P), or cash flow to price (C/P) as value stocks. Fama and French (1992, 1996) and Lakonishok, Shleifer, and Vishny (1994) show that for U.S. stocks there is a strong value premium in average returns. High B/M, E/P, or C/P stocks have higher average returns than low B/M, E/P, or C/P stocks. Fama and French (1995) and Lakonishok et al. (1994) also show that the value premium is associated with relative distress. High B/M, E/P, and C/P firms tend to have persistently low earnings; low B/M, E/P, and C/P stocks tend to be strong (growth) firms with persistently high earnings.

Lakonishok et al. (1994) and Haugen (1995) argued that the value premium in average returns arises because the market undervalues distressed stocks and overvalues growth stocks. When these pricing errors are corrected, distressed (value) stocks have high returns and growth stocks have low returns. In contrast, Fama and French (1993, 1995, 1996) argued that the value premium is compensation for risk missed by the capital asset pricing model (CAPM) of Sharpe (1964) and Lintneer (1965). This conclusion is based on evidence that there is common variation in the earnings of distressed firms that is not explained by market earnings, and there is common variation in the returns on distressed stocks that is not explained by the market return.

Most directly, including a risk factor for relative distress in a multifactor version of Merton's (1973) intertemporal capital asset pricing model (ICAMP) or Ross's (1976) arbitrage pricing theory (APT) captures the value premiums in U.S. returns generated by sorting stocks on B/M, E/P, C/P, or D/P (dividend yield).

Still another position, argued by Black (1993) and MacKinlay (1995), is that the value premium is sample-specific.

They presented additional out-of-sample evidence on the value premium. They examined two questions.

(i) Is there a value premium in markets outside the United States?

(ii) If so, does it conform to a risk model like the one that seems to describe U.S. returns?

There is existing evidence on (i). Chan, Hamao, and Lakonishok (1991) document a strong value premium in Japan. Capaul, Rowley, and Sharpe (1993) argue that the value premium is pervasive in international stock returns. Their sample period is, however, short (ten years).

The results are easily summarized. The value premium is indeed pervasive. One section shows that sorts of stocks in thirteen major markets on B/M, E/P, C/P, and D/P produce large value premiums for the 1975 to 1995 period. In another section they showed that an international two-factor version of Merton's (1973) ICAPM or Ross's (1976) APT seems to capture the value premium in the returns for major markets.

The CAPM versus a Two-Factor Model

In an international CAPM, all expected returns are explained by slopes on the global market return.

Like Solnik (1974), Harvey (1991), and others, they found little evidence against the international CAPM as a model for the returns on the market portfolios of countries.

The hypothesis that an international CAPM or ICAPM explains expected returns around the world does not require security returns to be correlated across countries. International asset pricing just says that the expected returns on assets are determined by their covariances with the global market return (CAPM and ICAPM) and the returns on global MMV portfolios needed to capture the effects of priced state variables (ICAPM).

Value and Growth in Emerging Markets

Emerging markets allow another out-of-sample test of the value premium. The International Finance Corporation (IFC) provides return, book-to-market equity, and earnings/price data for firms in more than thirty emerging markets. Although stock returns for some countries are available earlier, B/M and E/P data are not available until 1986. Thus, our sample period for emerging markets is for 1987 through 1995. Value stocks tend to have higher returns than growth stocks in markets around the world. Sorting on book-to-market equity, value stocks outperform growth stocks in twelve of thirteen major markets for a long period. There are similar value premiums when they sorted on earnings/price, cash flow/price, and dividend/price. There is also a value premium in emerging markets. Since these results are out-of-sample relative to earlier tests on U.S. data, they suggested that the return premium for value stocks is real.

An international CAPM cannot explain the value premium in international returns. But a one-state-variable international ICAPM (or a two-factor APT) that explains returns with the global market return and a risk factor for relative distress captures the value premium in country and global returns.

A reasonable conclusion, agnostic with respect to equilibrium asset pricing, is that a global market portfolio and a global portfolio formed to mimic relative distress are close to two-factor MMV in the limited set of portfolio opportunities covered by (i) global value and growth portfolios formed in various ways; and (ii) market, value, and growth portfolios of individual countries. In this view, the international two-factor model simply provides a parsimonious way to summarize the general patterns in international returns.

Author (s) / Year	**Factor Used**
Basu/1977	- Earnings/Price
Ball/1978	- Earnings/Price
Blume/1980	- Dividends/Price
Stattman/1980	- Book Equity/Market Equity
Banz/1981	- Market Equity
Reinganum/1981	-Beta - Earning/Price - Market Value

Basu/1983	- Earning/Price - Market Value
Cook & Rozeff/1984	- Market Value - Earnings/Price
Rosenberg, Reid & Lanstein/1985	- Book Equity/Market Equity
Banz & Breen 1986	- Market Value, Earnings/Price
Lakonishok & Shapiro/1986	- Beta - Earnings/Price - Market Value
Wilson/1986	- Cash Flow/Price
Bhandari/1988	- Total Assets/Market Equity - Total Assets/Book Equity
Chan & Chen/1988	- Market Equity
Keim/1988	- Earnings/Price
Jaffe, Keim & Westerfield/1989	- Earnings/Price - Market Equity
Ritter & Chopra/1989	- Market Value - Earnings/Price
Chan & Chen/1991	- Size - Leverage - Dividend changes

Chan, Hamao & Lakonishok/1991	- Book Equity/Market Equity - Earnings/Price - Market Equity
Fama & French/1992	- Size - Book Equity/Market Equity
Fama & French/1993	- A Value-Weighted Market Index - Size - Book Equity/Market Equity
Fama & French/1995	- Size - Book Equity/Market Equity
Daniel & Titman/1997	- Size - Book Equity/Market Equity
Asgharian & Hansson/2000	- A Value-Weighted Market Index - Book Equity/Market Equity - Leverage - Earning/price - Size - Past stock returns - Macroeconomic factors

Intersection and spanning refer to two important properties of portfolios.

1. A portfolio A of N assets is said to spann a narrower portfolio B of N_1 assets ($N_1<N$) if the efficient frontiers of the portfolios coincide. In other words, adding N-N_1 assets to portfolio B does not lead to a portfolio with superior mean-variance characteristics, i.e. higher mean returns per unit risk. This is the case when portfolio B can reproduce the characteristics of portfolio A and happens when the N-N_1 assets included in portfolio A but not in portfolio B as a group are highly correlated with the N_1 assets of portfolio B. Portfolio B does not span portfolio A when adding N-N_1 assets to portfolio B leads to a portfolio with superior mean-variance characteristics, i.e. the efficient frontier of portfolio B is included in the efficient frontier of portfolio A. In this case, portfolio B cannot reproduce the characteristics of portfolio A.

2. Intersection is a concept similar to spanning except that refers to portfolios of a specific investor, i.e. an investor with a given degree of risk aversion. If there is intersection between portfolio A and B for a specific degree of risk aversion, then investors with this degree of risk aversion are indifferent between portfolios A and B. In other words, adding N-N_1 assets to portfolio B does not lead to a portfolio with superior risk-return characteristics for this kind of investor.

Hence, we can either test the restriction for a specific η (hence λ), or for any η (hence λ). In the first case (intersection) we test whether for a specific investor, adding the SmB, HmL portfolios would lead to a portfolio, which is superior in terms of mean-variance characteristics. In the second case (spanning) we test whether for all investors (independent of their r), adding the SmB, HmL would lead to a portfolio which is superior in terms of mean-variance characteristics.

Intersection: Test whether for some specific n the condition $a=n(1-\beta)$ holds.

Spanning: Test whether for all n the condition $a=n(1-\beta)$ holds. This test implies in the 2-asset case considered: $\beta=1$, $\alpha=0$.

In order to test intersection and spanning, we can use the following system of OLS regressions:

$$_{2,t} = a + BR_{1,t} + _{ut}$$

Spanning corresponds to the null hypothesis: H_0: α=0, B_{iK}=0, i.e. $\alpha_1=\alpha_2=\ldots=\alpha_N=0$ and $b_1+b_2+\ldots+b_N=1$.

Spanning means that the mean-variance frontier of the K assets completely concides with the mean-variance frontier of the K+N assets. Intersection means that the two mean-variance frontiers have only one common point (portfolio).

In order to test intersection and spanning, we can use the following system of OLS regressions of excess returns:

$$R_{2,t} = a + BR_{1,t} + e_t$$

Intersection corresponds to the null hypothesis : H_0: $\alpha=0$, i.e. $\alpha_1=\alpha_2= \ldots = \alpha_N=0$.

Spanning corresponds to the null hypothesis: H_0: $\alpha = 0$, $B_{iK}=1$, i.e. $a_1 = \alpha_2=\ldots= \alpha_N = 0$ and $b_1 + b_2 + \ldots + b_N = 1$.

In order to test for intersection, we compute the Wald test statistic.

DATA

The data cover the period from July 1926 to December 2003 and consist of S&P returns. The data are collected from the database "Fama and French library". All information on accounting data, that is, book common equity, as well as on market capitalization, is also gathered from "Fama and French library".

This paper uses the time-series regression approach of Black, Jensen and Scholes (1972); monthly returns on SmB ,HmL, portfolios and mimicking portfolios for size (i.e. market capitalization ,SmB) and book-to-market equity (BE/ME,HmL).

The dependent variables in the time-series regressions are SmB, HmL.

- The independent variable is Rm-Rf, which means that this is the excess return, that is, weekly stock portfolios returns minus the three-month Treasury bill rate.

- The independent variable is Rm, which means that this is the row return, that is, weekly stock portfolios returns.

The purpose of the thesis is to test whether value and growth are important determinants of an optimal stock portfolio .We will try to explain whether to include or not portfolios like SmB,HmL into our basic portfolio. The model to estimate is the system:

1) for excess return $SmB=\alpha_1+\beta_1,Y$

and

$HmL= \alpha_2+\beta_2,Y$

2) and the system $SmB=\alpha_1+\beta_1,Y$

and for row return

$HmL= \alpha_2+\beta_2,Y$

R_p-R_f represents each time the returns in excess of the three-month Treasury bill rate for week t. R_{SMB} and R_{HML} are the returns on factor portfolios SMB and HML.

a_i is the unexplained expected return of stock portfolios

$\alpha_1,\alpha_2, \beta_1, \beta_2$ are the regression coefficients

Finally, e_t is the stochastic term that reflects all other variables mirroring risk factors in average stock-returns, but which are not included in the regression equation.

METHODOLOGY

The method applied to evaluate presented above is the ordinary least squares. For this purpose we used the Econometric View (Eviews) program, Version 3.

The regression coefficients measure the marginal contribution of the independent variables to the dependent variable, holding all other variables fixed.

Other coefficient results provided by the ordinary least squares (OLS) estimation method is the estimated standard errors. The standard errors measure the statistical reliability of the coefficient estimates – the larger the standard errors, the more statistical noise in the estimates.

The t-statistic, which is computed as the ratio of an estimated coefficient to its standard error, is used to test the hypothesis that a coefficient is equal to zero. To interpret the t-statistic, we should examine the probability of observing the t-statistic given that the coefficient is equal to zero.

Additionally, the OLS method provides some interesting statistics, which are summarized below:

The *R-squared* (R^2) statistic measures the success of the regression in predicting the values of the dependent variable within the sample. R^2 is the fraction of the variance of the dependent variable explained by the independent variables. The statistic will equal one if the regression fits perfectly, and zero if it fits no better than the simple mean of the dependent variable. It can be negative if the regression does not have an intercept or constant, or if the estimation method is two-stage least squares.

The *adjusted R^2*, commonly denoted as $\overline{R^2}$, penalizes the R^2 for the addition of regressors, which do not contribute to the explanatory power of the model. The R^2 is never larger than the R^2, can decrease as you add regressors, and for poorly fitting models, may be negative.

The *standard error of the regression* is a summary measure based on the estimated variance of the residuals. The sum of squared residuals can be used in a variety of statistical calculations.

Eviews reports the value of the log *likelihood* function (assuming normally distributed errors) evaluated at the estimated values of the coefficients. Likelihood ratio tests may be conducted by looking at the difference between the log likelihood values of the restricted and unrestricted versions of an equation.

The *F-statistic* tests the hypothesis that all of the slope coefficients (excluding the constant, or intercept) in a regression are zero. Under the null hypothesis with normally distributed errors, this statistic has an F-distribution with k-1 numerator degrees of freedom and T-k denominator degrees of freedom. The p-value given just below the F-statistic, denoted Prob(F-statistic), is the marginal significance level of the F-test. If the p-value is less than the significance level we are testing, say 0,05, we reject the null hypothesis that all slope coefficients are equal to zero. For the example above, the p-value is essentially zero, so we reject the null hypothesis that all of the regression coefficients are zero. Note that the F-test is a joint test so that even if all the t-statistics are insignificant, the F-statistic can be highly significant.

Table 1 – excess return

Refers to the period 1926:07 to 2003:12 with 930 observations - using the excess return Rm-Rf , Smb,HmL

Regarding the regression analysis (table 1) we observe that c (1) has t-stat 1,035925 less than 2 and c (2) has t-stat 10,39042 more than 2. On the other hand c (3) has a t-stat 2,654553 more than 2 and c (4) has a t-stat 6,290412 more than 2.These data implying the statistical significance for c (3) and c (4) with the t-stat more than two and the small probabilities.

After that we use the Wald test to measure how close the estimates come to satisfy the restrictions under the null hypothesis. E-Views reports a Chi-square statistic with associated p-values. In the intersection test we see that the probability is 0,018029 or 1,8% less than 5%. That means we reject the null hypothesis that there is intersection. So for all investors there is diversification benefit to include into their basic portfolio SmB and HmL portfolios.

In spanning test we see that the probability is almost zero for a significant level of 5% so we reject spanning hypothesis. That means all investors have diversification benefits and should include into their basic portfolio SmB and HmL portfolios.

Table 2-excess return a period

Refers to the period 1926:07 to 1939:12 with 162 observations - using the excess return Rm-Rf , Smb,HmL

Regarding the regression analysis (table 2) we observe that c (1) has t-stat 2,136077 more than 2 and c (2) has t-stat (2,065820) less than 2. On the other hand c (3) has a t-stat (0,028238) less than 2 and c (4) has a t-stat 0,1905202 less than 2.

With the Wald test we measure how close the estimates come to satisfy the restrictions under the null hypothesis. E-Views reports a Chi-square statistic with associated p-values. In the intersection test we see that the probability is 0,063249 or 6,32% more than 5%. That means we do not reject intersection (the null hypothesis). So, for all investors there is no diversification benefit to include into their basic portfolio SmB and HmL portfolios.

In spanning test we see that the probability is almost 0,119913 or 11,99% for a significance level of 5% so we cannot reject spanning hypothesis. That means all investors have no diversification benefits and should not include into their basic portfolio SmB and HmL portfolios.

Table 3 - excess return b period

Refers to the period 1940:01 to 1969:12 with 360 observations - using the excess return Rm-Rf , Smb,HmL

Regarding the regression analysis (table 3) we observe that c (1) has t-stat 0,667254 less than 2 and c (2) has t-stat 6,435776 more than 2. C (3) has a t-stat 2,742421 more than 2 and c (4) has a t-stat 4,609514 more than 2.Three of the coefficients have probability almost zero and t-stat more than two, so all these data implying the statistical significance of these variables.

With the Wald test we measure how close the estimates come to satisfy the restrictions under the null hypothesis. E-Views reports a Chi-square statistic with associated p-values. In the intersection test we see that the probability is 0,022398 or 2,2398% less than 5%. That means we reject intersection (the null hypothesis). So, for all investors there is diversification benefit to include into their basic portfolio SmB and HmL portfolios.

In spanning test we see that the probability is zero for a significance level of 5% so we reject spanning hypothesis. That means all investors have diversification benefits and should include into their basic portfolio SmB and HmL portfolios.

Table 4 - excess return c period

Refers to the period 1970:01 to 2003:12 with 408 observations - using the excess return Rm-Rf , Smb,HmL

Regarding the regression analysis (table 4) we observe that c (1) has t-stat 0,489901 less than 2 and c (2) has t-stat 5,566349 more than 2. C (3) has a t-stat 4,418499 more than 2 and c (4) has a t-stat (1,021759) less than 2.Two of the coefficients have probability almost zero so these data implying the statistical significance of these two variables.

With the Wald test we measure how close the estimates come to satisfy the restrictions under the null hypothesis. E-Views reports a Chi-square statistic with associated p-values. In the intersection test we see that the probability is 0,00019 or 0,019% less than 5%. That means we reject intersection (the null hypothesis). So, for all investors there is diversification benefit to include into their basic portfolio SmB and HmL portfolios.

In spanning test we see that the probability is zero for a significance level of 5% so we reject spanning hypothesis. That means all investors have diversification benefits and should include into their basic portfolio SmB and HmL portfolios.

Table 5 – row return

Refers to the period 1926:07 to 2003:12 with 930 observations - using the row return Rm, Smb, HmL

Regarding the regression analysis (table 5) we observe that c (1) has t-stat 0,473974 less than 2 and c (2) has t-stat 1,031158 less than 2. On the other hand c (3) has a t-stat 2,285000 more than 2 and c (4) has a t-stat 6,334341 more than 2.We observe that there is statistical significance for c (3), c(4) with the high t-stat and the low probability .

We test with the Wald test how close the estimates come to satisfy the restrictions under the null hypothesis. E-Views reports a Chi-square statistic with associated p-values. In the intersection test we see

- For n=0,02 degree of risk aversion the probability is 0,097419 or 9,7419% less than 10%. That means we reject intersection (the null hypothesis). If Ho is rejected then it is worth for the investor with the degree of risk aversion corresponding to 0,02 to add assets SmB and HmL into his portfolio.

- For n=0,03 degree of risk aversion the probability is 0,115873 or 11,5873% more than 10%. That means we do not reject intersection (the null hypothesis). If Ho is not rejected then it is not worth for the investor with the degree of risk aversion corresponding to 0,03 to add assets SmB and HmL into his portfolio.

- For n=0,04 degree of risk aversion the probability is 0,136239 or 13,6239% more than 10%. That means we do not reject intersection (the null hypothesis). If Ho is not rejected then it is not worth for the investor with the degree of risk aversion corresponding to 0,04 to add assets SmB and HmL into his portfolio.

In spanning test we see that the probability is zero for a significance level of 10% so we reject spanning hypothesis. That means all investors have diversification benefits and should not include into their basic portfolio SmB and HmL portfolios.

Table 6 - row return a period

Refers to the period 1926:07 to 1939:12 with 162 observations - using the row return a period Rm, Smb, HmL

Regarding the regression analysis (table 6) we observe that c (1) has t-stat 0,716465 less than 2 and c (2) has t-stat 5,122448 more than 2. On the other hand c (3) has a t-stat (0,635659) less than 2 and c (4) has a t-stat 9,956031 more than 2.We can see the statistical significance for factors C (2) and C (3) with the high t-stat and the low probabilities.

With the Wald test we test how close the estimates come to satisfy the restrictions under the null hypothesis. E-Views reports a Chi-square statistic with associated p-values.

- For n=0,02 degree of risk aversion the probability is 0,577134 or 57,7134% more than 10%. That means we cannot reject intersection (the null hypothesis). If Ho is not rejected then it is not worth for the investor with the degree of risk aversion corresponding to 0,02 to add assets SmB and HmL into his portfolio.

- For n=0,03 degree of risk aversion the probability is 0,579633 or 57,963% more than 10%. That means we cannot reject intersection (the null hypothesis). If Ho is not rejected then it is not worth for the investor with the degree of risk aversion corresponding to 0,03 to add assets SmB and HmL into his portfolio.

- For n=0,04 degree of risk aversion the probability is 0,136239 or 13,6239% more than 10%. That means we cannot reject intersection (the null hypothesis). If Ho is not rejected then it is not worth for the investor with the degree of risk aversion corresponding to 0,02 to add assets SmB and HmL into his portfolio.

In spanning test we see that the probability is zero for a significance level of 10% so we reject spanning hypothesis. If Ho is rejected then it is worth for all investors to add into their portfolio assets SmB and HmL

Table 7 - row return b period

Refers to the period 1940:01 to 1969:12 with 360 observations - using the row return b period Rm, Smb, HmL

Regarding the regression analysis (table 7) we observe that c (1) has t-stat 0,395973 less than 2 and c (2) has t-stat 6,459398 more than 2. On the other hand c (3) has a t-stat 2,544159 more than 2 and c (4) has a t-stat 4,543725 more than 2.We can see the statistical significance for factors C (2), C (3) and C (4) with the high t-stat and the low probabilities.

With the Wald test we test how close the estimates come to satisfy the restrictions under the null hypothesis. E-Views reports a Chi-square statistic with associated p-values.

- For n=0,02 degree of risk aversion the probability is 0,054796 or 5,4796% less than 10%. That means we reject intersection (the null hypothesis).If Ho is rejected then it is worth for the investor with the degree of risk aversion corresponding to 0,02 to add assets SmB and HmL into his portfolio.

- For n=0,03 degree of risk aversion the probability is 0,063901 or 6,3901% less than 10%. That means we reject intersection (the null hypothesis). If Ho is rejected then it is worth for the investor with the degree of risk aversion corresponding to 0,03 to add assets SmB and HmL into his portfolio.

- For n=0,04 degree of risk aversion the probability is 0,073891 or 7,3891% less than 10%. That means we reject intersection (the null hypothesis). If Ho is rejected then it is worth for the investor with the degree of risk aversion corresponding to 0,04 to add assets SmB and HmL into his portfolio.

In spanning test we see that the probability is zero for a significance level of 10% so we reject spanning hypothesis. If Ho is rejected then it is worth for all investors to add into their portfolio assets SmB and HmL .

Table 8 - row return c period

Refers to the period 1970:01 to 2003:12 with 408 observations - using the row return c period Rm, Smb, HmL

Regarding the regression analysis (table 8) we observe that c (1) has t-stat (0,102408) less than 2 and c (2) has t-stat 5,513322 more than 2. On the other hand c (3) has a t-stat 5,431643 more than 2 and c (4) has a t-stat (1,019615) less than 2.We can see the statistical significance for factors C (2), C (3) with the high t-stat and the low probabilities.

With the Wald test we test how close the estimates come to satisfy the restrictions under the null hypothesis. E-Views reports a Chi-square statistic with associated p-values.

- For n=0,02 degree of risk aversion the probability is 0,000001 less than 10%. That means we reject intersection (the null hypothesis).If Ho is rejected then it is worth for the investor with the degree of risk aversion corresponding to 0,02 to add assets SmB and HmL into his portfolio.

- For n=0,03 degree of risk aversion the probability is 0,000001 less than 10%. That means we reject intersection (the null hypothesis). If Ho is rejected then it is worth for the investor with the degree of risk aversion corresponding to 0,03 to add assets SmB and HmL into his portfolio.

- For n=0,04 degree of risk aversion the probability is 0,000002 less than 10%. That means we reject intersection (the null hypothesis). If Ho is rejected then it is worth for the investor with the degree of risk aversion corresponding to 0,04 to add assets SmB and HmL into his portfolio.

In spanning test we see that the probability is zero for a significance level of 10% so we reject spanning hypothesis. If Ho is rejected then it is worth for any investor with any degree of risk aversion to add into their portfolio assets SmB and HmL .

Bibliography

1. Fama E.F. & French K.R.: "The cross-section of expected stock returns", The Journal of Finance 47 (1992).

2. Fama E.F. & French K.R.: "Common risk factors in the returns on stocks and bonds", The Journal of Financial Economics 33 (1993).

3. Fama E.F. & French K.R.: "Size and book-to-market factors in earnings and returns", The Journal of Finance 50 (1995).

4. Fama E.F. & French K.R.: "Multifactor explanations of asset pricing anomalies", The Journal of Finance 51 (1996).

5. Fama E.F. & French K.R.: "The equity premium", The Journal of Finance, April 2002.

6. Fama E.F. & French K.R.: "The conditional CAPM and the cross-section of expected returns".

7. Fama E.F. & French K.R.: "Value versus Growth: The international evidence"

8. W. Sharpe, Gordon Alexander, Jeffery Bailey: "Investments"

9. James L. Davis, Eugene F. Fama, and Kenneth R. French, Characteristics, Covariances, and Average Returns: 1929 to 1997, The Journal of Finance, Vol LV, No 1, February 2000.

10. Kenneth L. Fisher, Joseph L. Toms and W. Kevin Blount (1995), "Driving Factors Behind Style-Based Investing", In R. Klein and J. Lederman, eds., Equity Style Management. Burr Ridge, IL: Irwin, 1995.

11. Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian Investment, extrapolation, and risk, Journal of Finance 49, 1541-1578.

12. Marc R. Reinganum, "A Revival of the Small-Firm Effect", The Journal of Portfolio Management, spring 1992, pp. 55-62.

13. William F. Sharpe, "Asset allocation: Management style and performance measurement" The journal of Portfolio Management, Winter 1992, pp. 7-19.

APPENDIX

TABLE 1

System: REGRESSION - Excess return
Estimation Method: Seemingly Unrelated Regression
Date: 06/16/04 Time: 23:18
Sample: 1926:07 2003:12
Included observations: 930
Total system (balanced) observations 1860

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.108949	0.105171	1.035.925	0.3004
C(2)	0.197097	0.018969	1.039.042	0.0000
C(3)	0.309062	0.116427	2.654.553	0.0080
C(4)	0.132094	0.020999	6.290.412	0.0000

Determinant residual covariance 1.261.589

Equation: SMB=C(1)+C(2)*Y
Observations: 930

R-squared	0.104013	Mean dependent var	0.236054
Adjusted R-squared	0.103047	S.D. dependent var	3.367.149
S.E. of regression	3.188.946	Sum squared resid	9.437.184
Durbin-Watson stat	2.029.026		

Equation: HML=C(3)+C(4)*Y
Observations: 930

R-squared	0.040811	Mean dependent var	0.394247
Adjusted R-squared	0.039778	S.D. dependent var	3.602.628
S.E. of regression	3.530.249	Sum squared resid	11565.35
Durbin-Watson stat	1.662.271		

INTERSECTION

Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)=0 C(3)=0		
Chi-square	8.031.498	Probability	0.018029

SPANNING

Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)=0 C(3)=0 C(2)=1 C(4)=1		
Chi-square	3.462.861	Probability	0.000000

TABLE 2

System: REGRESSION - Excess return a period
Estimation Method: Seemingly Unrelated Regression
Date: 06/17/04 Time: 17:54
Sample: 1926:07 1939:12
Included observations: 162
Total system (balanced) observations 324

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.104.697	0.517161	2.136.077	0.0334
C(2)	-6.053.024	2.930.083	-2.065.820	0.0397
C(3)	-0.017700	0.626815	-0.028238	0.9775
C(4)	0.676539	3.551.345	0.190502	0.8490
Determinant residual covariance		8.282.397		

Equation: SMB=C(1)+C(2)*Y
Observations: 162

R-squared	0.025667	Mean dependent var	0.420556
Adjusted R-squared	0.019578	S.D. dependent var	5.137.787
S.E. of regression	5.087.246	Sum squared resid	4.140.811
Durbin-Watson stat	1.947.915		

Equation: HML=C(3)+C(4)*Y
Observations: 162

R-squared	0.000224	Mean dependent var	0.058765
Adjusted R-squared	-0.006025	S.D. dependent var	6.147.399
S.E. of regression	6.165.889	Sum squared resid	6.082.910
Durbin-Watson stat	1.488.187		

INTERSECTION

Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)=0 C(3)=0		
Chi-square	5.340.106	Probability	0.069249

SPANNING

Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)=0 C(3)=0 C(2)=1 C(4)=1		
Chi-square	7.320.005	Probability	0.119913

TABLE 3

System: REGRESSION - Excess return b period
Estimation Method: Seemingly Unrelated Regression
Date: 06/18/04 Time: 15:06
Sample: 1940:01 1969:12
Included observations: 360
Total system (balanced) observations 720

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.074169	0.111155	0.667254	0.5048
C(2)	0.183362	0.028491	6.435.776	0.0000
C(3)	0.334176	0.121855	2.742.421	0.0063
C(4)	0.143972	0.031234	4.609.514	0.0000
Determinant residual covariance		2.113.314		

Equation: SMB=C(1)+C(2)*Y
Observations: 360

R-squared	0.103182	Mean dependent var	0.229889
Adjusted R-squared	0.100677	S.D. dependent var	2.176.659
S.E. of regression	2.064.184	Sum squared resid	1.525.386
Durbin-Watson stat	1.676.648		

Equation: HML=C(3)+C(4)*Y
Observations: 360

R-squared	0.055732	Mean dependent var	0.456444
Adjusted R-squared	0.053094	S.D. dependent var	2.325.456
S.E. of regression	2.262.880	Sum squared resid	1.833.185
Durbin-Watson stat	1.837.499		

INTERSECTION

Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)=0		
	C(3)=0		
Chi-square	7.597.601	Probability	0.022398

SPANNING

Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)=0		
	C(3)=0		
	C(2)=1		
	C(4)=1		
Chi-square	1.414.668	Probability	0.000000

TABLE 4

System: REGRESSION - Excess return c period
Estimation Method: Seemingly Unrelated Regression
Date: 06/18/04 Time: 14:28
Sample: 1970:01 2003:12
Included observations: 408
Total system (balanced) observations 816

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.078689	0.160623	0.489901	0.6243
C(2)	0.189751	0.034089	5.566.349	0.0000
C(3)	0.615011	0.139190	4.418.499	0.0000
C(4)	-0.301830	0.029540	-1.021.759	0.0000
Determinant residual covariance		7.778.370		

Equation: SMB=C(1)+C(2)*Y
Observations: 408

R-squared	0.070582	Mean dependent var	0.168235
Adjusted R-squared	0.068292	S.D. dependent var	3.352.557
S.E. of regression	3.236.055	Sum squared resid	4.251.654
Durbin-Watson stat	2.081.940		

Equation: HML=C(3)+C(4)*Y
Observations: 408

R-squared	0.203746	Mean dependent var	0.472574
Adjusted R-squared	0.201784	S.D. dependent var	3.138.743
S.E. of regression	2.804.244	Sum squared resid	3.192.696
Durbin-Watson stat	1.750.955		

INTERSECTION

Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)=0 C(3)=0		
Chi-square	2.169.340	Probability	0.000019

SPANNING

Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)=0 C(3)=0 C(2)=1 C(4)=1		
Chi-square	3.103.751	Probability	0.000000

TABLE 5

System: REGRESSION - Row return
Estimation Method: Seemingly Unrelated Regression
Date: 06/22/04 Time: 12:27
Sample: 1926:07 2003:12
Included observations: 930
Total system (balanced) observations 1860

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.050279	0.106080	0.473974	0.6356
C(2)	0.196319	0.019039	1.031.158	0.0000
C(3)	0.268049	0.117308	2.285.000	0.0224
C(4)	0.133361	0.021054	6.334.341	0.0000
Determinant residual covariance		1.262.853		

Equation: SMB=C(1)+C(2)*Y
Observations: 930

R-squared	0.102601	Mean dependent var	0.236054
Adjusted R-squared	0.101634	S.D. dependent var	3.367.149
S.E. of regression	3.191.457	Sum squared resid	9.452.048
Durbin-Watson stat	2.027.081		

Equation: HML=C(3)+C(4)*Y
Observations: 930

R-squared	0.041360	Mean dependent var	0.394247
Adjusted R-squared	0.040327	S.D. dependent var	3.602.628
S.E. of regression	3.529.240	Sum squared resid	11558.74
Durbin-Watson stat	1.662.934		

INTERSECTION FOR n=0,02
Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)-0.02*(1-C(2))=0 C(3)-0.02*(1-C(4))=0		
Chi-square	4.655.993	Probability	0.097491

INTERSECTION FOR n=0,03
Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)-0.03*(1-C(2))=0 C(3)-0.03*(1-C(4))=0		
Chi-square	4.310.519	Probability	0.115873

INTERSECTION FOR n=0,04
Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)-0.04*(1-C(2))=0 C(3)-0.04*(1-C(4))=0		
Chi-square	3.986.694	Probability	0.136239

Wald Test:
System: SPANNING

Null Hypothesis:	C(1)=0		
	C(3)=0		
	C(2)=1		
	C(4)=1		
Chi-square	3.488.026	Probability	0.000000

TABLE 6

System: REGRESSION - Row return a period
Estimation Method: Seemingly Unrelated Regression
Date: 06/22/04 Time: 13:53
Sample: 1926:07 1939:12
Included observations: 162
Total system (balanced) observations 324

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.268314	0.374497	0.716465	0.4742
C(2)	0.205852	0.040186	5.122.448	0.0000
C(3)	-0.241836	0.380449	-0.635659	0.5255
C(4)	0.406455	0.040825	9.956.031	0.0000
Determinant residual covariance		5.086.424		

Equation: SMB=C(1)+C(2)*Y
Observations: 162

R-squared	0.139394	Mean dependent var	0.420556
Adjusted R-squared	0.134015	S.D. dependent var	5.137.787
S.E. of regression	4.781.137	Sum squared resid	3.657.484
Durbin-Watson stat	2.095.758		

Equation: HML=C(3)+C(4)*Y
Observations: 162

R-squared	0.379602	Mean dependent var	0.058765
Adjusted R-squared	0.375724	S.D. dependent var	6.147.399
S.E. of regression	4.857.129	Sum squared resid	3.774.673
Durbin-Watson stat	1.612.152		

Wald Test:INTERSECTION FOR n=0,02
System: REGRESSION

Null Hypothesis:	C(1)-0.02*(1-C(2))=0 C(3)-0.02*(1-C(4))=0		
Chi-square	1.099.362	Probability	0.577134

Wald Test:INTERSECTION FOR n=0,03
System: REGRESSION

Null Hypothesis:	C(1)-0.03*(1-C(2))=0 C(3)-0.03*(1-C(4))=0		
Chi-square	1.090.720	Probability	0.579633

Wald Test:INTERSECTION FOR n=0,04
System: REGRESSION

Null Hypothesis:	C(1)-0.04*(1-C(2))=0 C(3)-0.04*(1-C(4))=0		
Chi-square	1.083.259	Probability	0.581800

Wald Test:
System: SPANNING

Null Hypothesis:	C(1)=0		
	C(3)=0		
	C(2)=1		
	C(4)=1		
Chi-square	5.178.904	Probability	0.000000

TABLE 7

System: REGRESSION - Row return b period
Estimation Method: Seemingly Unrelated Regression
Date: 06/22/04 Time: 14:13
Sample: 1940:01 1969:12
Included observations: 360
Total system (balanced) observations 720

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.044422	0.112185	0.395973	0.6922
C(2)	0.185271	0.028682	6.459.398	0.0000
C(3)	0.313256	0.123128	2.544.159	0.0112
C(4)	0.143037	0.031480	4.543.725	0.0000
Determinant residual covariance		2.114.565		

Equation: SMB=C(1)+C(2)*Y
Observations: 360

R-squared	0.103862	Mean dependent var	0.229889
Adjusted R-squared	0.101359	S.D. dependent var	2.176.659
S.E. of regression	2.063.401	Sum squared resid	1.524.229
Durbin-Watson stat	1.687.202		

Equation: HML=C(3)+C(4)*Y
Observations: 360

R-squared	0.054238	Mean dependent var	0.456444
Adjusted R-squared	0.051596	S.D. dependent var	2.325.456
S.E. of regression	2.264.670	Sum squared resid	1.836.085
Durbin-Watson stat	1.831.867		

INTERSECTION FOR n=0,02

Wald Test:

System: REGRESSION

Null Hypothesis:	C(1)-0.02*(1-C(2))=0 C(3)-0.02*(1-C(4))=0		
Chi-square	5.808.275	Probability	0.054796

INTERSECTION FOR n=0,03

Wald Test:

System: REGRESSION

Null Hypothesis:	C(1)-0.03*(1-C(2))=0 C(3)-0.03*(1-C(4))=0		
Chi-square	5.500.835	Probability	0.063901

INTERSECTION FOR n=0,04

Wald Test:

System: REGRESSION

Null Hypothesis:	C(1)-0.04*(1-C(2))=0 C(3)-0.04*(1-C(4))=0		
Chi-square	5.210.319	Probability	0.073891

Wald Test:
System: SPANNING

Null Hypothesis:	C(1)=0		
	C(3)=0		
	C(2)=1		
	C(4)=1		
Chi-square	1.416.556	Probability	0.000000

TABLE 8

System: REGRESSION - Row return c period
Estimation Method: Seemingly Unrelated Regression
Date: 06/22/04 Time: 14:43
Sample: 1970:01 2003:12
Included observations: 408
Total system (balanced) observations 816

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.016734	0.163404	-0.102408	0.9185
C(2)	0.188735	0.034232	5.513.322	0.0000
C(3)	0.768932	0.141565	5.431.643	0.0000
C(4)	-0.302391	0.029657	-1.019.615	0.0000
Determinant residual covariance		7.791.124		

Equation: SMB=C(1)+C(2)*Y
Observations: 408

R-squared	0.069336	Mean dependent var	0.168235
Adjusted R-squared	0.067044	S.D. dependent var	3.352.557
S.E. of regression	3.238.223	Sum squared resid	4.257.352
Durbin-Watson stat	2.078.808		

Equation: HML=C(3)+C(4)*Y
Observations: 408

R-squared	0.203065	Mean dependent var	0.472574
Adjusted R-squared	0.201102	S.D. dependent var	3.138.743

INTERSECTION FOR n=0,02
Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)-0.02*(1-C(2))=0 C(3)-0.02*(1-C(4))=0		
Chi-square	2.849.688	Probability	0.000001

INTERSECTION FOR n=0,03
Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)-0.03*(1-C(2))=0 C(3)-0.03*(1-C(4))=0		
Chi-square	2.743.015	Probability	0.000001

INTERSECTION FOR n=0,04
Wald Test:
System: REGRESSION

Null Hypothesis:	C(1)-0.04*(1-C(2))=0 C(3)-0.04*(1-C(4))=0		
Chi-square	2.638.855	Probability	0.000002

Wald Test:
System: SPANNING

Null Hypothesis:	C(1)=0		
	C(3)=0		
	C(2)=1		
	C(4)=1		
Chi-square	3.133.057	Probability	0.000000